Model Selection

```
library(ISLR)
summary(Hitters)
```

```
##      AtBat            Hits         HmRun            Runs
##  Min.   : 16.0   Min.   :  1   Min.   : 0.00   Min.   :  0.00
##  1st Qu.:255.2   1st Qu.: 64   1st Qu.: 4.00   1st Qu.: 30.25
##  Median :379.5   Median : 96   Median : 8.00   Median : 48.00
##  Mean   :380.9   Mean   :101   Mean   :10.77   Mean   : 50.91
##  3rd Qu.:512.0   3rd Qu.:137   3rd Qu.:16.00   3rd Qu.: 69.00
##  Max.   :687.0   Max.   :238   Max.   :40.00   Max.   :130.00
##
##       RBI             Walks            Years            CAtBat
##  Min.   :  0.00   Min.   :  0.00   Min.   : 1.000   Min.   :   19.0
##  1st Qu.: 28.00   1st Qu.: 22.00   1st Qu.: 4.000   1st Qu.:  816.8
##  Median : 44.00   Median : 35.00   Median : 6.000   Median : 1928.0
##  Mean   : 48.03   Mean   : 38.74   Mean   : 7.444   Mean   : 2648.7
##  3rd Qu.: 64.75   3rd Qu.: 53.00   3rd Qu.:11.000   3rd Qu.: 3924.2
##  Max.   :121.00   Max.   :105.00   Max.   :24.000   Max.   :14053.0
##
##      CHits            CHmRun           CRuns             CRBI
##  Min.   :   4.0   Min.   :  0.00   Min.   :   1.0   Min.   :   0.00
##  1st Qu.: 209.0   1st Qu.: 14.00   1st Qu.: 100.2   1st Qu.:  88.75
##  Median : 508.0   Median : 37.50   Median : 247.0   Median : 220.50
##  Mean   : 717.6   Mean   : 69.49   Mean   : 358.8   Mean   : 330.12
##  3rd Qu.:1059.2   3rd Qu.: 90.00   3rd Qu.: 526.2   3rd Qu.: 426.25
##  Max.   :4256.0   Max.   :548.00   Max.   :2165.0   Max.   :1659.00
##
##      CWalks        League  Division    PutOuts          Assists
##  Min.   :   0.00   A:175   E:157    Min.   :   0.0   Min.   :  0.0
##  1st Qu.:  67.25   N:147   W:165    1st Qu.: 109.2   1st Qu.:  7.0
##  Median : 170.50                    Median : 212.0   Median : 39.5
##  Mean   : 260.24                    Mean   : 288.9   Mean   :106.9
##  3rd Qu.: 339.25                    3rd Qu.: 325.0   3rd Qu.:166.0
##  Max.   :1566.00                    Max.   :1378.0   Max.   :492.0
##
##      Errors          Salary       NewLeague
##  Min.   : 0.00   Min.   :  67.5   A:176
##  1st Qu.: 3.00   1st Qu.: 190.0   N:146
##  Median : 6.00   Median : 425.0
##  Mean   : 8.04   Mean   : 535.9
##  3rd Qu.:11.00   3rd Qu.: 750.0
##  Max.   :32.00   Max.   :2460.0
##                  NA's   :59
```

There are some missing values here, so before we proceed we will remove them:

```
Hitters <- na.omit(Hitters)
with(Hitters,sum(is.na(Salary)))
```

```
## [1] 0
```

Best Subset regression

We will now use the package `leaps` to evaluate all the best-subset models.

```
library(leaps)
regfit.full <- regsubsets(Salary~.,data=Hitters)
summary(regfit.full)
```

```
## Subset selection object
## Call: regsubsets.formula(Salary ~ ., data = Hitters)
## 19 Variables  (and intercept)
##            Forced in Forced out
## AtBat          FALSE      FALSE
## Hits           FALSE      FALSE
## HmRun          FALSE      FALSE
## Runs           FALSE      FALSE
## RBI            FALSE      FALSE
## Walks          FALSE      FALSE
## Years          FALSE      FALSE
## CAtBat         FALSE      FALSE
## CHits          FALSE      FALSE
## CHmRun         FALSE      FALSE
## CRuns          FALSE      FALSE
## CRBI           FALSE      FALSE
## CWalks         FALSE      FALSE
## LeagueN        FALSE      FALSE
## DivisionW      FALSE      FALSE
## PutOuts        FALSE      FALSE
## Assists        FALSE      FALSE
## Errors         FALSE      FALSE
## NewLeagueN     FALSE      FALSE
## 1 subsets of each size up to 8
## Selection Algorithm: exhaustive
##          AtBat Hits HmRun Runs RBI Walks Years CAtBat CHits CHmRun CRuns
## 1  ( 1 ) " "   " "  " "   " "  " " " "   " "   " "    " "   " "    " "
## 2  ( 1 ) " "   "*"  " "   " "  " " " "   " "   " "    " "   " "    " "
## 3  ( 1 ) " "   "*"  " "   " "  " " " "   " "   " "    " "   " "    " "
## 4  ( 1 ) " "   "*"  " "   " "  " " " "   " "   " "    " "   " "    " "
## 5  ( 1 ) "*"   "*"  " "   " "  " " " "   " "   " "    " "   " "    " "
## 6  ( 1 ) "*"   "*"  " "   " "  " " "*"   " "   " "    " "   " "    " "
## 7  ( 1 ) " "   "*"  " "   " "  " " "*"   " "   "*"    "*"   "*"    " "
## 8  ( 1 ) "*"   "*"  " "   " "  " " "*"   " "   " "    " "   "*"    "*"
##          CRBI CWalks LeagueN DivisionW PutOuts Assists Errors NewLeagueN
## 1  ( 1 ) "*"  " "    " "     " "       " "     " "     " "    " "
## 2  ( 1 ) "*"  " "    " "     " "       " "     " "     " "    " "
## 3  ( 1 ) "*"  " "    " "     " "       "*"     " "     " "    " "
## 4  ( 1 ) "*"  " "    " "     "*"       "*"     " "     " "    " "
## 5  ( 1 ) "*"  " "    " "     "*"       "*"     " "     " "    " "
## 6  ( 1 ) "*"  " "    " "     "*"       "*"     " "     " "    " "
## 7  ( 1 ) " "  " "    " "     "*"       "*"     " "     " "    " "
## 8  ( 1 ) " "  "*"    " "     "*"       "*"     " "     " "    " "
```

It gives by default best-subsets up to size 8; lets increase that to 19, i.e. all the variables

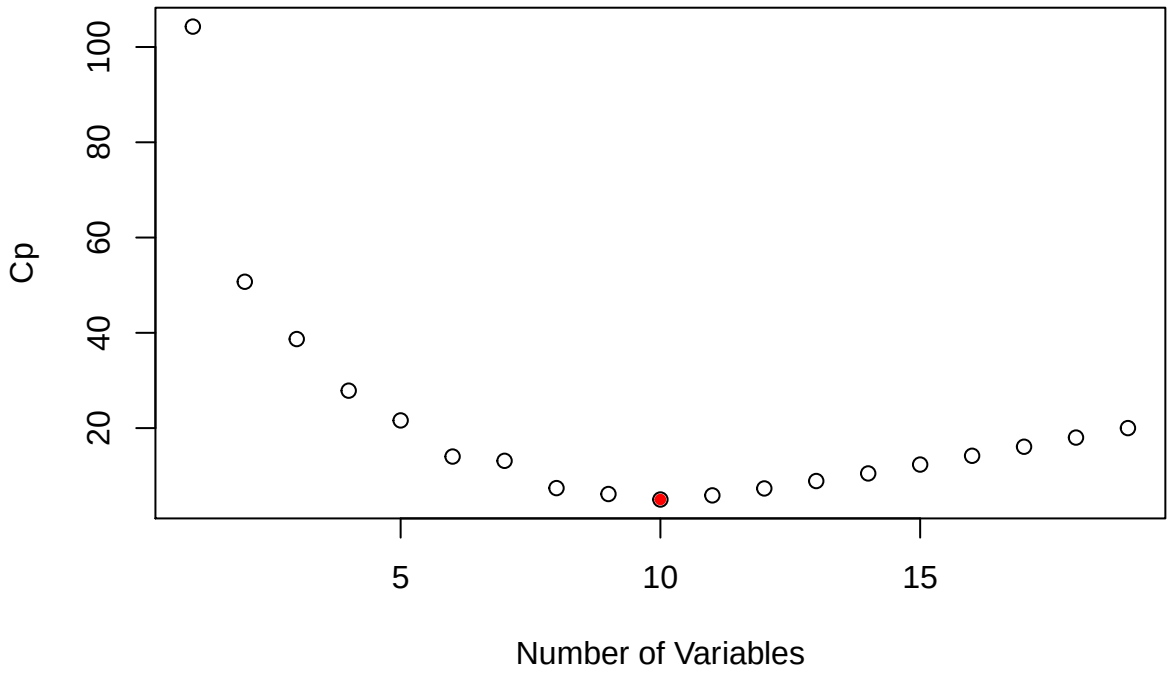
```
regfit.full <- regsubsets(Salary~.,data=Hitters, nvmax=19)
reg.summary <- summary(regfit.full)
names(reg.summary)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

```
plot(reg.summary$cp,xlab="Number of Variables",ylab="Cp")
which.min(reg.summary$cp)
```

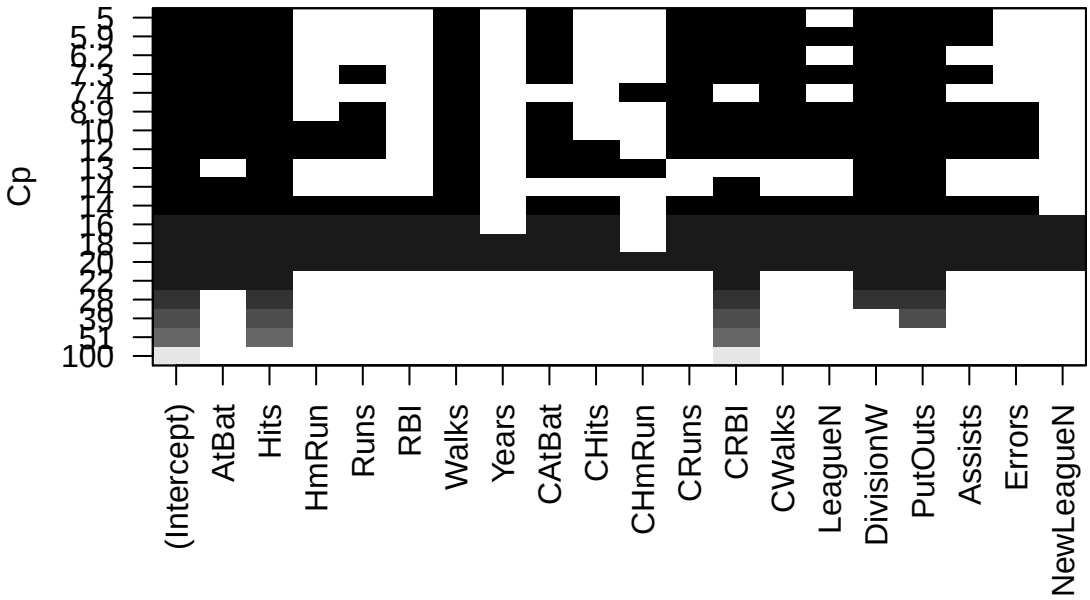
```
## [1] 10
```

```
points(10,reg.summary$cp[10],pch=20,col="red")
```



There is a plot method for the `regsubsets` object

```
plot(regfit.full,scale="Cp")
```




```
coef(regfit.full,10)
```

```
##  (Intercept)        AtBat         Hits        Walks       CAtBat
##  162.5354420   -2.1686501    6.9180175    5.7732246   -0.1300798
##        CRuns         CRBI       CWalks    DivisionW      PutOuts
##    1.4082490    0.7743122   -0.8308264 -112.3800575    0.2973726
##      Assists
##    0.2831680
```

Forward Stepwise Selection

Here we use the `regsubsets` function but specify the 'method="forward" option:

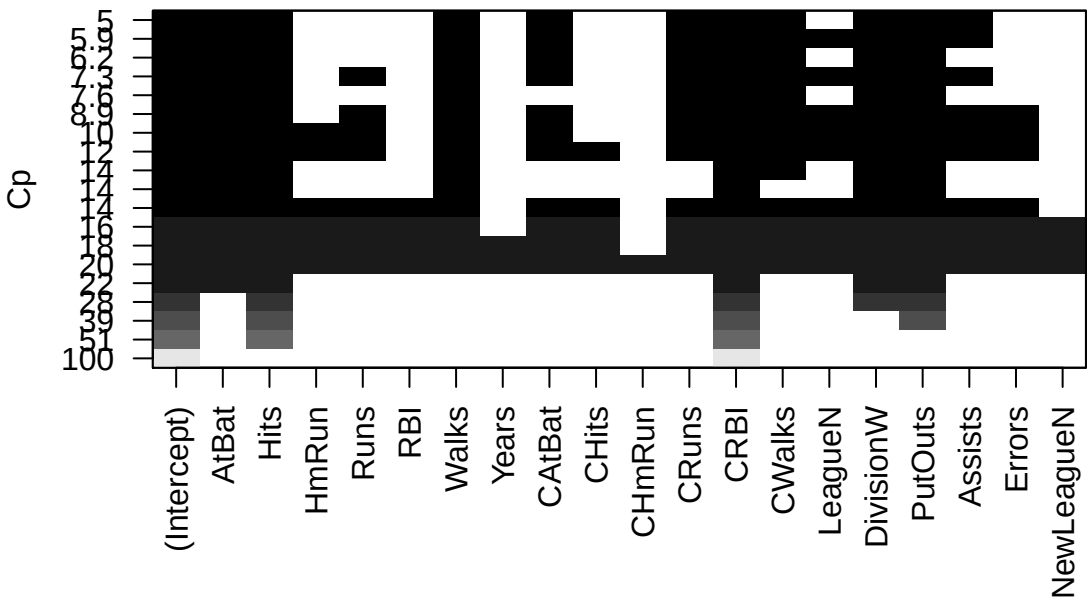
```
regfit.fwd <- regsubsets(Salary~.,data=Hitters,nvmax=19,method="forward")
summary(regfit.fwd)
```

```
## Subset selection object
## Call: regsubsets.formula(Salary ~ ., data = Hitters, nvmax = 19, method = "forward")
## 19 Variables  (and intercept)
##           Forced in Forced out
## AtBat         FALSE      FALSE
## Hits          FALSE      FALSE
## HmRun         FALSE      FALSE
## Runs          FALSE      FALSE
## RBI           FALSE      FALSE
## Walks         FALSE      FALSE
```

```
## Years           FALSE      FALSE
## CAtBat          FALSE      FALSE
## CHits           FALSE      FALSE
## CHmRun          FALSE      FALSE
## CRuns           FALSE      FALSE
## CRBI            FALSE      FALSE
## CWalks          FALSE      FALSE
## LeagueN         FALSE      FALSE
## DivisionW       FALSE      FALSE
## PutOuts         FALSE      FALSE
## Assists         FALSE      FALSE
## Errors          FALSE      FALSE
## NewLeagueN      FALSE      FALSE
## 1 subsets of each size up to 19
## Selection Algorithm: forward
##           AtBat Hits HmRun Runs RBI Walks Years CAtBat CHits CHmRun CRuns
## 1  ( 1 )  " "   " "  " "   " "  " " " " " "   " "   " "   " "    " "    " "
## 2  ( 1 )  " "   "*"  " "   " "  " " " " " "   " "   " "   " "    " "    " "
## 3  ( 1 )  " "   "*"  " "   " "  " " " " " "   " "   " "   " "    " "    " "
## 4  ( 1 )  " "   "*"  " "   " "  " " " " " "   " "   " "   " "    " "    " "
## 5  ( 1 )  "*"   "*"  " "   " "  " " " " " "   " "   " "   " "    " "    " "
## 6  ( 1 )  "*"   "*"  " "   " "  " " " " "*"   " "   " "   " "    " "    " "
## 7  ( 1 )  "*"   "*"  " "   " "  " " " " "*"   " "   " "   " "    " "    " "
## 8  ( 1 )  "*"   "*"  " "   " "  " " " " "*"   " "   " "   " "    " "    "*"
## 9  ( 1 )  "*"   "*"  " "   " "  " " " " "*"   " "   "*"   " "    " "    "*"
## 10  ( 1 ) "*"   "*"  " "   " "  " " " " "*"   " "   "*"   " "    " "    "*"
## 11  ( 1 ) "*"   "*"  " "   " "  " " " " "*"   " "   "*"   " "    " "    "*"
## 12  ( 1 ) "*"   "*"  " "   "*"  " " " " "*"   " "   "*"   " "    " "    "*"
## 13  ( 1 ) "*"   "*"  " "   "*"  " " " " "*"   " "   "*"   " "    " "    "*"
## 14  ( 1 ) "*"   "*"  "*"   "*"  " " " " "*"   " "   "*"   " "    " "    "*"
## 15  ( 1 ) "*"   "*"  "*"   "*"  " " " " "*"   " "   "*"   "*"    " "    "*"
## 16  ( 1 ) "*"   "*"  "*"   "*"  "*" "*" "*"   " "   "*"   "*"    " "    "*"
## 17  ( 1 ) "*"   "*"  "*"   "*"  "*" "*" "*"   " "   "*"   "*"    " "    "*"
## 18  ( 1 ) "*"   "*"  "*"   "*"  "*" "*" "*"   "*"   "*"   "*"    " "    "*"
## 19  ( 1 ) "*"   "*"  "*"   "*"  "*" "*" "*"   "*"   "*"   "*"    "*"    "*"
##           CRBI CWalks LeagueN DivisionW PutOuts Assists Errors NewLeagueN
## 1  ( 1 )  "*"  " "    " "     " "       " "     " "     " "    " "
## 2  ( 1 )  "*"  " "    " "     " "       " "     " "     " "    " "
## 3  ( 1 )  "*"  " "    " "     " "       "*"     " "     " "    " "
## 4  ( 1 )  "*"  " "    " "     "*"       "*"     " "     " "    " "
## 5  ( 1 )  "*"  " "    " "     "*"       "*"     " "     " "    " "
## 6  ( 1 )  "*"  " "    " "     "*"       "*"     " "     " "    " "
## 7  ( 1 )  "*"  "*"    " "     "*"       "*"     " "     " "    " "
## 8  ( 1 )  "*"  "*"    " "     "*"       "*"     " "     " "    " "
## 9  ( 1 )  "*"  "*"    " "     "*"       "*"     " "     " "    " "
## 10  ( 1 ) "*"  "*"    " "     "*"       "*"     "*"     " "    " "
## 11  ( 1 ) "*"  "*"    "*"     "*"       "*"     "*"     " "    " "
## 12  ( 1 ) "*"  "*"    "*"     "*"       "*"     "*"     " "    " "
## 13  ( 1 ) "*"  "*"    "*"     "*"       "*"     "*"     "*"    " "
## 14  ( 1 ) "*"  "*"    "*"     "*"       "*"     "*"     "*"    " "
## 15  ( 1 ) "*"  "*"    "*"     "*"       "*"     "*"     "*"    " "
## 16  ( 1 ) "*"  "*"    "*"     "*"       "*"     "*"     "*"    " "
## 17  ( 1 ) "*"  "*"    "*"     "*"       "*"     "*"     "*"    "*"
## 18  ( 1 ) "*"  "*"    "*"     "*"       "*"     "*"     "*"    "*"
```

```
## 19  ( 1 ) "*"  "*"    "*"     "*"       "*"     "*"     "*"     "*"
```

```
plot(regfit.fwd,scale="Cp")
```



Model Selection Using a Validation Set

Lets make a training and validation set, so that we can choose a good subset model. We will do it using a slightly different approach from what was done in the the book.

```
dim(Hitters)
```

```
## [1] 263  20
```

```
set.seed(1)
train <- sample(seq(263),180,replace=FALSE)
train
```

```
##   [1]  70  98 150 237  53 232 243 170 161  16 259  45 173  97 192 124 178
##  [18] 245  94 190 228  52 158  31  64  92   4  91 205  80 113 140 115  43
##  [35] 244 153 181  25 163  93 184 144 174 122 117 251   6 104 241 149 102
##  [52] 183 224 242  15  21  66 107 136  83 186  60 211  67 130 210  95 151
##  [69]  17 256 207 162 200 239 236 168 249  73 222 177 234 199 203  59 235
##  [86]  37 126  22 230 226  42  11 110 214 132 134  77  69 188 100 206  58
## [103]  44 159 101  34 208  75 185 201 261 112  54  65  23   2 106 254 257
## [120] 154 142  71 166 221 105  63 143  29 240 212 167 172   5  84 120 133
## [137]  72 191 248 138 182  74 179 135  87 196 157 119  13  99 263 125 247
## [154]  50  55  20  57   8  30 194 139 238  46  78  88  41   7  33 141  32
```

```
## [171] 180 164 213  36 215  79 225 229 198  76
```

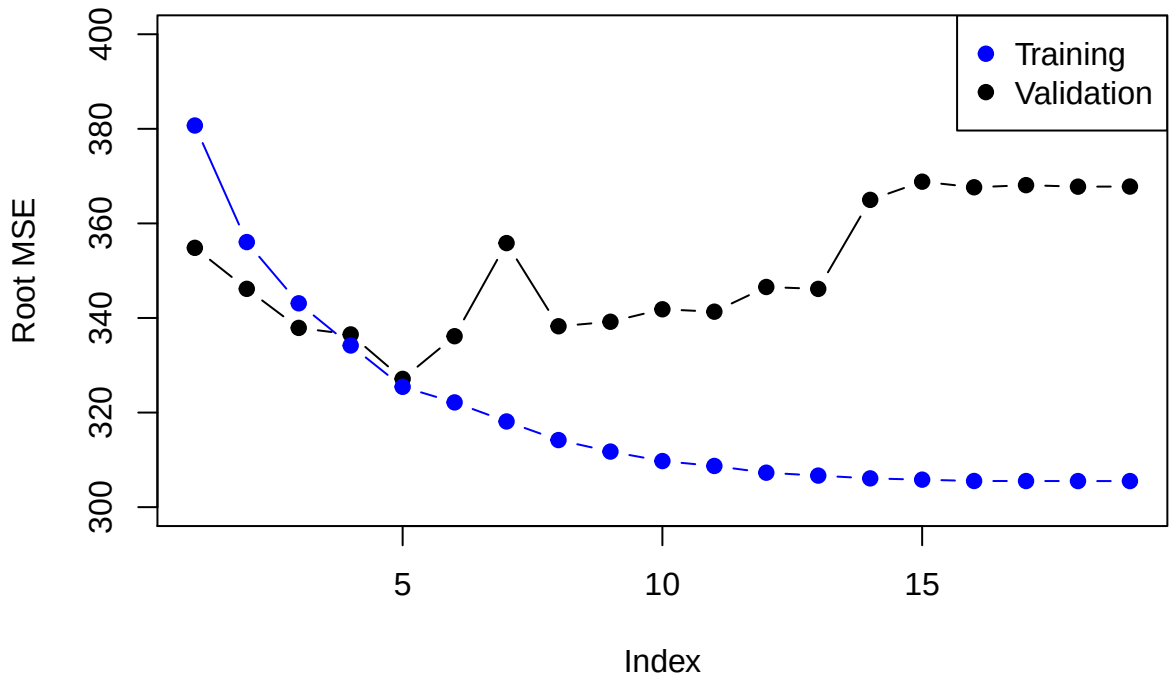
```
regfit.fwd <- regsubsets(Salary~.,data=Hitters[train,],nvmax=19,method="forward")
```

Now we will make predictions on the observations not used for training. We know there are 19 models, so we set up some vectors to record the errors. We have to do a bit of work here, because there is no predict method for `regsubsets`.

```
val.errors <- rep(NA,19)
x.test <- model.matrix(Salary~.,data=Hitters[-train,])# notice the -index!

for(i in 1:19){
  coefi <- coef(regfit.fwd,id=i)
  pred <- x.test[,names(coefi)]%*%coefi
  val.errors[i] <- mean((Hitters$Salary[-train]-pred)^2)
}

plot(sqrt(val.errors),ylab="Root MSE",ylim=c(300,400),pch=19,type="b")
points(sqrt(regfit.fwd$rss[-1]/180),col="blue",pch=19,type="b")
legend("topright",legend=c("Training","Validation"),col=c("blue","black"),pch=19)
```



As we expect, the training error goes down monotonically as the model gets bigger, but not so for the validation error.

This was a little tedious - not having a predict method for `regsubsets`. So we will write one!

```
predict.regsubsets <- function(object,newdata,id,...){
                        form <- as.formula(object$call[[2]])
                        mat <- model.matrix(form,newdata)
```

```
                        coefi <- coef(object,id=id)
                        mat[,names(coefi)]%*%coefi
}
```

Model Selection by Cross-Validation

We will do 10-fold cross-validation. Its really easy!

```
set.seed(11)
folds <- sample(rep(1:10,length=nrow(Hitters)))
folds
```

```
##   [1]  3  1  4  4  7  7  3  5  5  2  5  2  8  3  3  3  9  2  9  8 10  5  8
##  [24]  5  5  5  5 10 10  4  4  7  6  7  7  7  3  4  8  3  6  8 10  4  3  9
##  [47]  9  3  4  9  8  7 10  6 10  3  6  9  4  2  8  2  5  6 10  7  2  8  8
##  [70]  1  3  6  2  5  8  1  1  2  8  1 10  1  2  3  6  6  5  8  8 10  4  2
##  [93]  6  1  7  4  8  3  7  8  7  1 10  1  6  2  9 10  1  7  7  4  7  4 10
## [116]  3  6 10  6  6  9  8 10  6  7  9  6  7  1 10  2  2  5  9  9  6  1  1
## [139]  2  9  4 10  5  3  7  7 10 10  9  3  3  7  3  1  4  6  6 10  4  9  9
## [162]  1  3  6  8 10  8  5  4  5  6  2  9 10  3  7  7  6  6  2  3  2  4  4
## [185]  4  4  8  2  3  5  9  9 10  2  1  3  9  6  7  3  1  9  4 10 10  8  8
## [208]  8  2  5  9  8 10  5  8  2  4  1  4  4  5  5  2  1  9  5  2  9  9  5
## [231]  3  2  1  9  1  7  2  5  8  1  1  7  6  6  4  5 10  5  7  4  8  6  9
## [254]  1  2  5  7  1  3  1  3  1  2
```

```
table(folds)
```

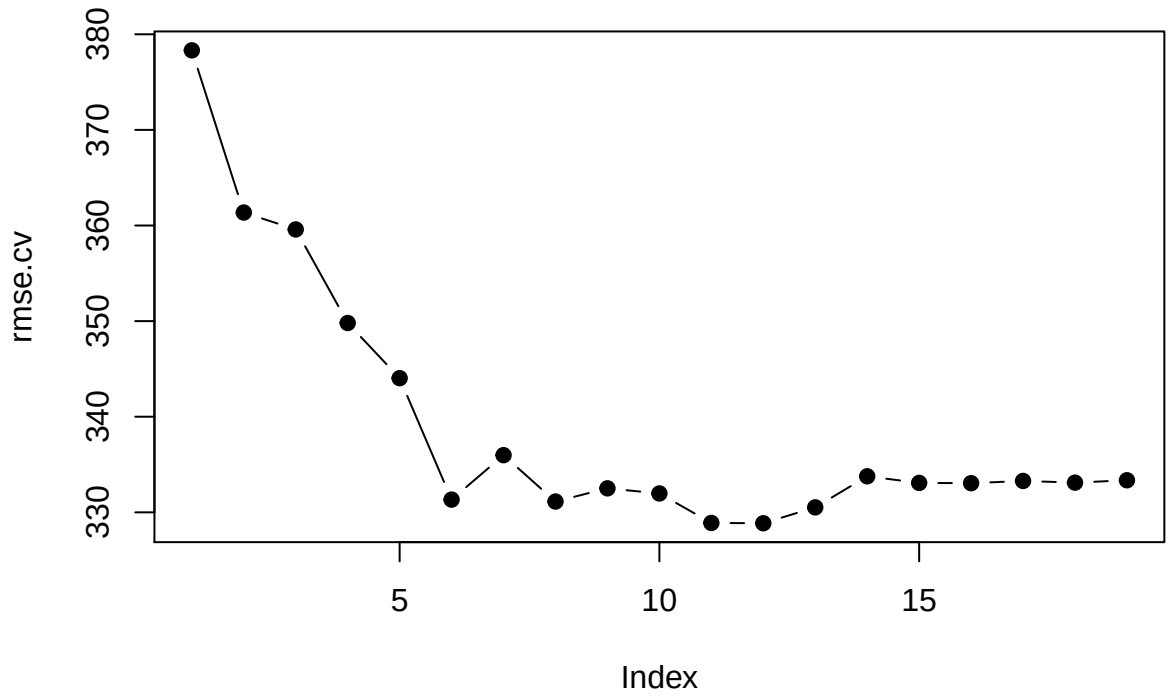
```
## folds
##  1  2  3  4  5  6  7  8  9 10
## 27 27 27 26 26 26 26 26 26 26
```

```
cv.errors <- matrix(NA,10,19)

for(k in 1:10){
best.fit <- regsubsets(Salary~.,data=Hitters[folds!=k,],nvmax=19,method="forward")
  for(i in 1:19){
                pred <- predict(best.fit,Hitters[folds==k,],id=i)
                cv.errors[k,i] <- mean( (Hitters$Salary[folds==k]-pred)^2)
  }
}

rmse.cv <- sqrt(apply(cv.errors,2,mean))

plot(rmse.cv,pch=19,type="b")
```



Ridge Regression and the Lasso

We will use the package `glmnet`, which does not use the model formula language, so we will set up an `x` and `y`.

```
library(glmnet)
```

```
## Loading required package: Matrix
```

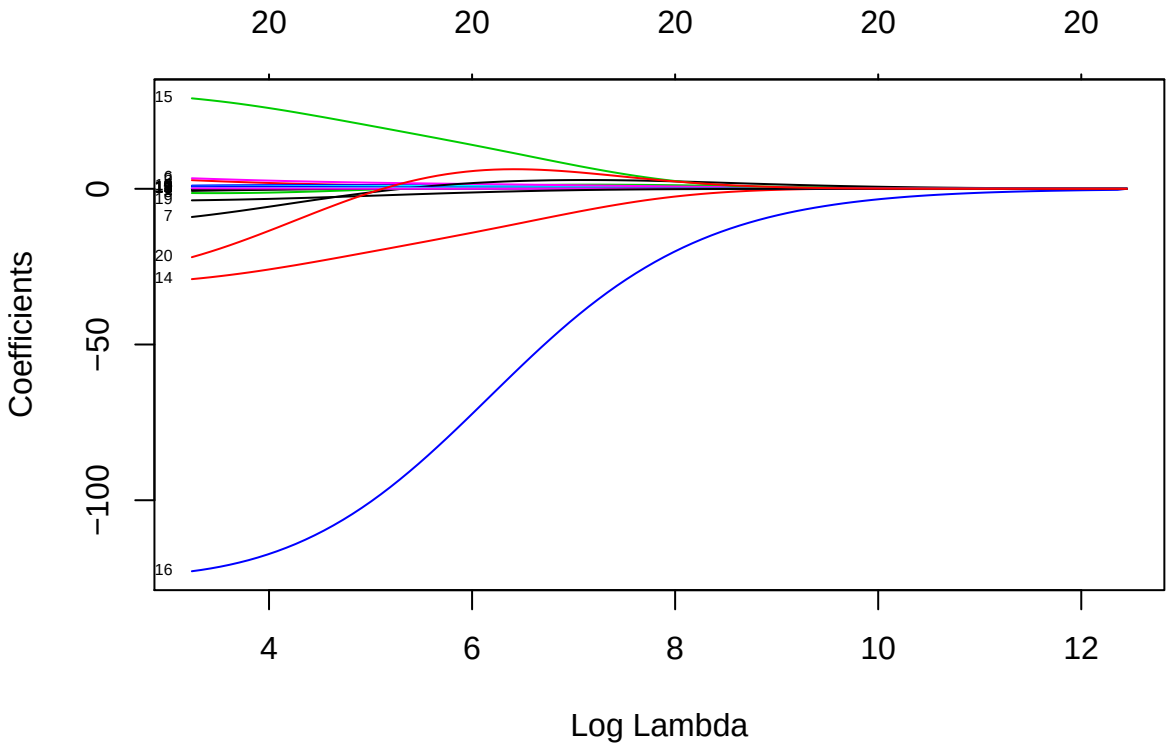
```
## Loading required package: foreach
```

```
## Loaded glmnet 2.0-10
```

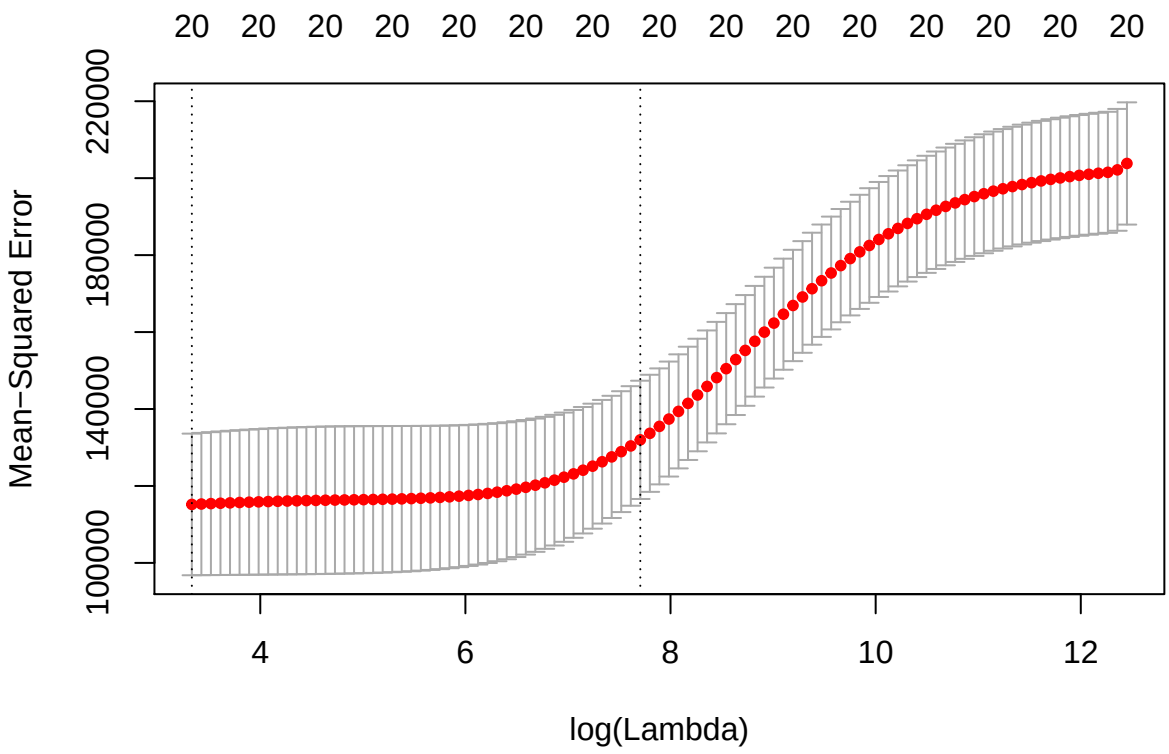
```
x <- model.matrix(Salary~.-1,data=Hitters)
y <- Hitters$Salary
```

First we will fit a ridge-regression model. This is achieved by calling `glmnet` with `alpha=0` (see the helpfile). There is also a `cv.glmnet` function which will do the cross-validation for us.

```
fit.ridge <- glmnet(x,y,alpha=0)
plot(fit.ridge,xvar="lambda",label=TRUE)
```

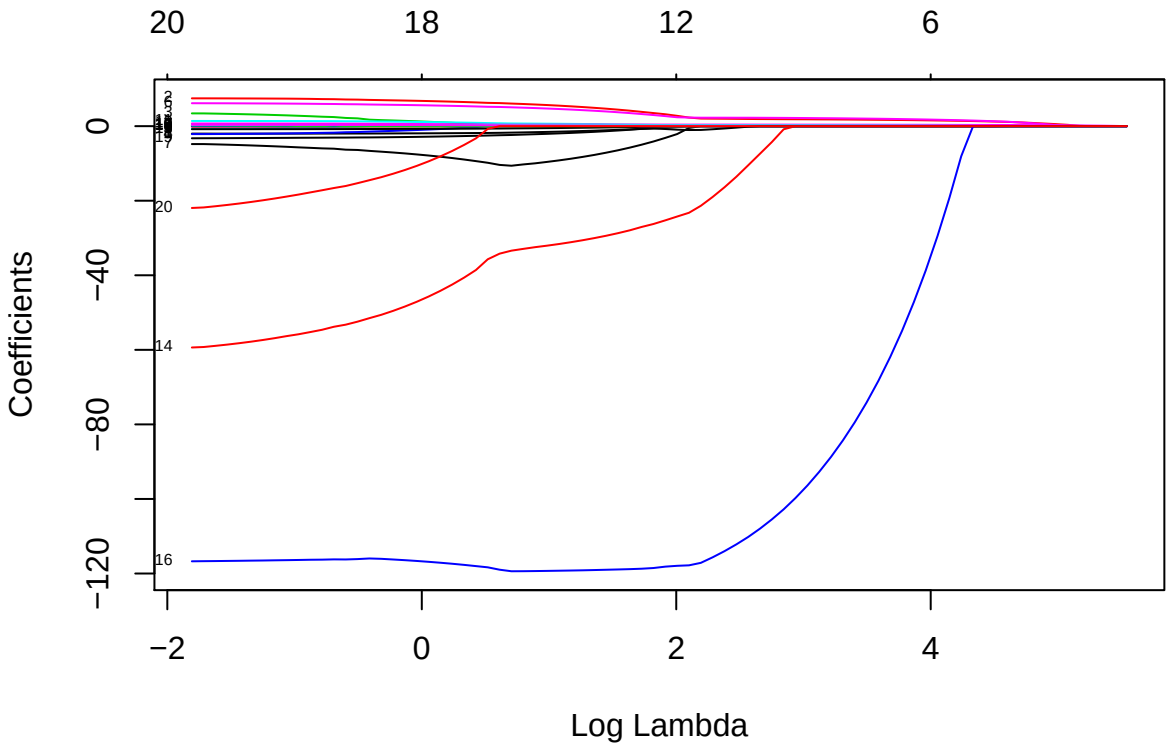



```
cv.ridge <- cv.glmnet(x,y,alpha=0)
plot(cv.ridge)
```

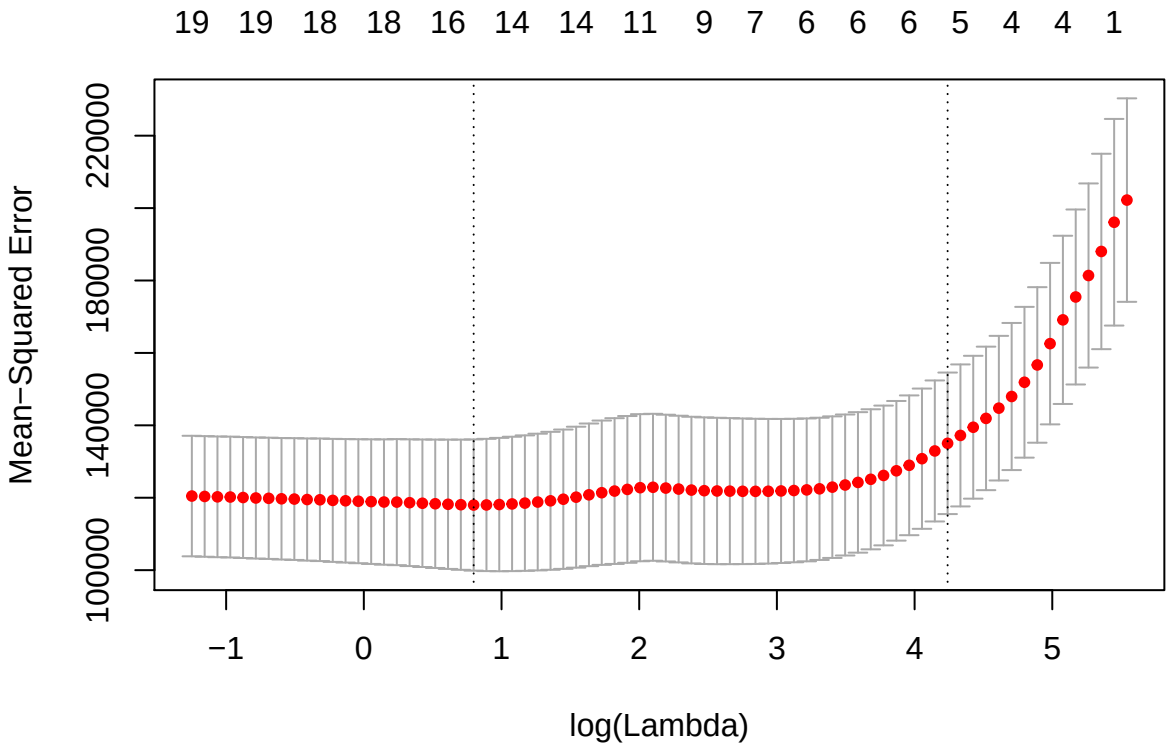


Now we fit a lasso model; for this we use the default `alpha=1`

```
fit.lasso <- glmnet(x,y)
plot(fit.lasso,xvar="lambda",label=TRUE)
```




```
cv.lasso <- cv.glmnet(x,y)
plot(cv.lasso)
```




```
coef(cv.lasso)
```

```
## 21 x 1 sparse Matrix of class "dgCMatrix"
##                            1
## (Intercept) 127.95694754
## AtBat         .
## Hits          1.42342566
## HmRun         .
## Runs          .
## RBI           .
## Walks         1.58214111
## Years         .
## CAtBat        .
## CHits         .
## CHmRun        .
## CRuns         0.16027975
## CRBI          0.33667715
## CWalks        .
## LeagueA       .
## LeagueN       .
## DivisionW    -8.06171262
## PutOuts       0.08393604
## Assists       .
## Errors        .
## NewLeagueN    .
```

Suppose we want to use our earlier train/validation division to select the `lambda` for the lasso.This is easy to

do.

```
lasso.tr <- glmnet(x[train,],y[train])
lasso.tr
```

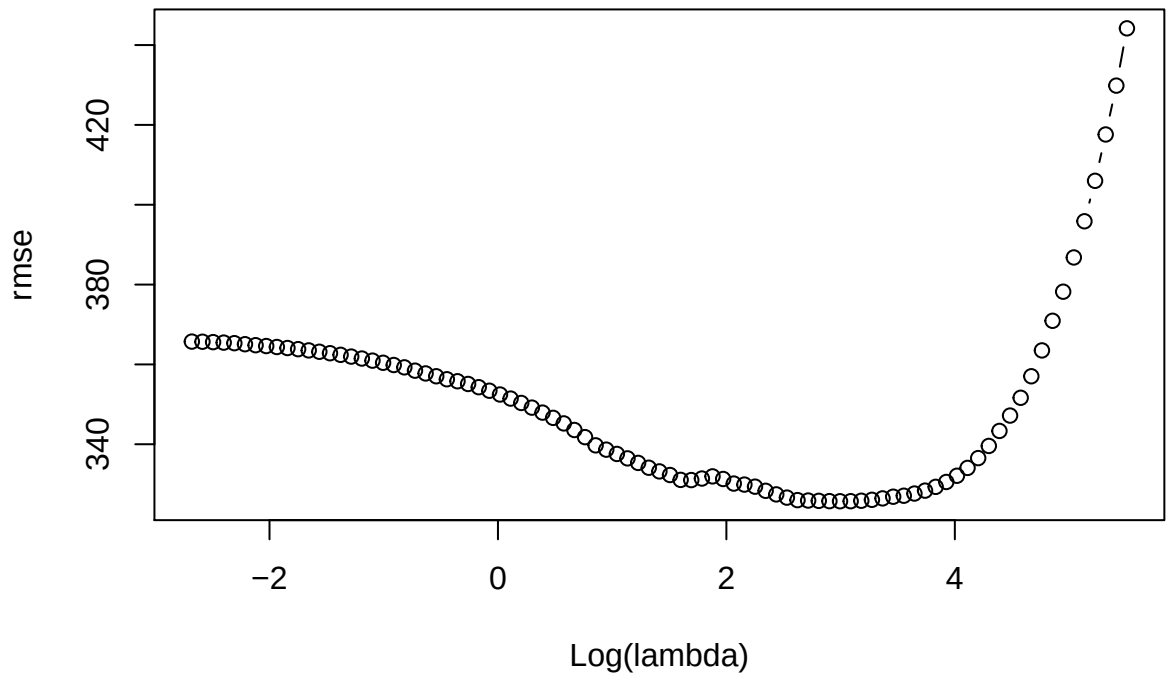
```
##
## Call:  glmnet(x = x[train, ], y = y[train])
##
##        Df    %Dev    Lambda
##   [1,]  0 0.00000 246.40000
##   [2,]  1 0.05013 224.50000
##   [3,]  1 0.09175 204.60000
##   [4,]  2 0.13840 186.40000
##   [5,]  2 0.18000 169.80000
##   [6,]  3 0.21570 154.80000
##   [7,]  3 0.24710 141.00000
##   [8,]  3 0.27320 128.50000
##   [9,]  4 0.30010 117.10000
##  [10,]  4 0.32360 106.70000
##  [11,]  4 0.34310  97.19000
##  [12,]  4 0.35920  88.56000
##  [13,]  5 0.37360  80.69000
##  [14,]  5 0.38900  73.52000
##  [15,]  5 0.40190  66.99000
##  [16,]  5 0.41260  61.04000
##  [17,]  5 0.42140  55.62000
##  [18,]  5 0.42880  50.67000
##  [19,]  5 0.43490  46.17000
##  [20,]  5 0.43990  42.07000
##  [21,]  5 0.44410  38.33000
##  [22,]  5 0.44760  34.93000
##  [23,]  6 0.45140  31.83000
##  [24,]  7 0.45480  29.00000
##  [25,]  7 0.45770  26.42000
##  [26,]  7 0.46010  24.07000
##  [27,]  8 0.46220  21.94000
##  [28,]  8 0.46380  19.99000
##  [29,]  8 0.46520  18.21000
##  [30,]  8 0.46630  16.59000
##  [31,]  8 0.46730  15.12000
##  [32,]  8 0.46810  13.78000
##  [33,]  9 0.47110  12.55000
##  [34,]  9 0.47380  11.44000
##  [35,]  9 0.47620  10.42000
##  [36,] 10 0.48050   9.49500
##  [37,]  9 0.48450   8.65200
##  [38,] 10 0.48770   7.88300
##  [39,] 10 0.49360   7.18300
##  [40,] 11 0.49890   6.54500
##  [41,] 12 0.50450   5.96300
##  [42,] 12 0.51010   5.43400
##  [43,] 13 0.51470   4.95100
##  [44,] 13 0.51850   4.51100
##  [45,] 13 0.52170   4.11000
##  [46,] 14 0.52440   3.74500
```

```
## [47,] 14 0.52670   3.41200
## [48,] 15 0.52870   3.10900
## [49,] 15 0.53030   2.83300
## [50,] 15 0.53160   2.58100
## [51,] 16 0.53280   2.35200
## [52,] 17 0.53420   2.14300
## [53,] 18 0.53580   1.95300
## [54,] 18 0.53760   1.77900
## [55,] 18 0.53890   1.62100
## [56,] 18 0.54000   1.47700
## [57,] 18 0.54090   1.34600
## [58,] 18 0.54160   1.22600
## [59,] 18 0.54220   1.11700
## [60,] 18 0.54280   1.01800
## [61,] 18 0.54320   0.92770
## [62,] 18 0.54360   0.84530
## [63,] 18 0.54380   0.77020
## [64,] 19 0.54410   0.70180
## [65,] 19 0.54430   0.63940
## [66,] 19 0.54450   0.58260
## [67,] 19 0.54470   0.53090
## [68,] 19 0.54490   0.48370
## [69,] 20 0.54510   0.44070
## [70,] 20 0.54520   0.40160
## [71,] 20 0.54530   0.36590
## [72,] 20 0.54540   0.33340
## [73,] 20 0.54550   0.30380
## [74,] 20 0.54560   0.27680
## [75,] 20 0.54570   0.25220
## [76,] 20 0.54570   0.22980
## [77,] 20 0.54580   0.20940
## [78,] 20 0.54580   0.19080
## [79,] 20 0.54590   0.17380
## [80,] 20 0.54590   0.15840
## [81,] 20 0.54590   0.14430
## [82,] 20 0.54590   0.13150
## [83,] 20 0.54600   0.11980
## [84,] 19 0.54600   0.10920
## [85,] 19 0.54600   0.09948
## [86,] 19 0.54600   0.09064
## [87,] 19 0.54600   0.08259
## [88,] 20 0.54600   0.07525
## [89,] 20 0.54600   0.06856
```

```
pred <- predict(lasso.tr,x[-train,])
dim(pred)
```

```
## [1] 83 89
```

```
rmse <-  sqrt(apply((y[-train]-pred)^2,2,mean))
plot(log(lasso.tr$lambda),rmse,type="b",xlab="Log(lambda)")
```




```
lam.best <- lasso.tr$lambda[order(rmse)[1]]
lam.best
```

```
## [1] 19.98706
```

```
coef(lasso.tr,s=lam.best)
```

```
## 21 x 1 sparse Matrix of class "dgCMatrix"
##                          1
## (Intercept)  107.9416686
## AtBat          .
## Hits           0.1591252
## HmRun          .
## Runs           .
## RBI            1.7340039
## Walks          3.4657091
## Years          .
## CAtBat         .
## CHits          .
## CHmRun         .
## CRuns          0.5386855
## CRBI           .
## CWalks         .
## LeagueA      -30.0493021
## LeagueN        .
## DivisionW   -113.8317016
## PutOuts        0.2915409
```

```
## Assists         .
## Errors          .
## NewLeagueN     2.0367518
```