

Linear Models & Regularization

By: Udit (based on ISLR)

Setup

Using **Hitters** dataset from **ISLR2** package. Using **Leaps** package with **regsubsets** for Best Subset Selection. Using **glmnet** package with **glmnet()** for Lasso & Ridge shrinkage. Using **pls** package with **pcr()** for Principal Components regression and **plsr()** for Partial Least Square regression.

```
library(ISLR2)
library(glmnet)
```

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

```
## Loaded glmnet 4.1-2
```

```
library(leaps)
library(pls)
```

```
##
```

```
## Attaching package: 'pls'
```

```
## The following object is masked from 'package:stats':
```

```
##
```

```
##      loadings
```

```
# Data Review
```

```
names(Hitters)
```

```
## [1] "AtBat"      "Hits"       "HmRun"      "Runs"       "RBI"        "Walks"
## [7] "Years"      "CAtBat"     "CHits"      "CHmRun"     "CRuns"      "CRBI"
## [13] "CWalks"     "League"     "Division"   "PutOuts"    "Assists"    "Errors"
## [19] "Salary"     "NewLeague"
```

```
dim(Hitters)
```

```
## [1] 322 20
```

```
summary(Hitters) # Salary has missing values
```

```
##      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
```

```
sum(is.na(Hitters$Salary))
```

```
## [1] 59
```

```
# Drop missing values
d_Hitters = na.omit(Hitters)
dim(d_Hitters)
```

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

Best Subset Selection

Looks through 2^p models, and identifies best model for each value of p . An asterisk indicates that a given variable is included in the corresponding model.

```
regfit.full <- regsubsets(Salary ~., d_Hitters, nvmax=dim(d_Hitters)-1) #nvmax=8 by default
summary(regfit.full)
```

```
## Subset selection object
## Call: regsubsets.formula(Salary ~ ., d_Hitters, nvmax = dim(d_Hitters) -
##      1)
## 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: exhaustive
##      AtBat Hits HmRun Runs RBI Walks Years CAtBat CHits CHmRun CRuns CRBI
## 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 ) "*" "*" "*" "*" "*" "*" "*" "*" "*" "*" " " " " "*" "*"
##      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 ) "*" "*" "*" "*" "*" "*" "*" "*"

```

```
names(summary(regfit.full))
```

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

```
#summary(regfit.full)$rsq
#summary(regfit.full)$adjr2
summary(regfit.full)$bic
```

```
## [1] -90.84637 -128.92622 -135.62693 -141.80892 -144.07143 -147.91690
## [7] -145.25594 -147.61525 -145.44316 -143.21651 -138.86077 -133.87283
## [13] -128.77759 -123.64420 -118.21832 -112.81768 -107.35339 -101.86391
## [19] -96.30412
```

```
reg.summary = summary(regfit.full)
```

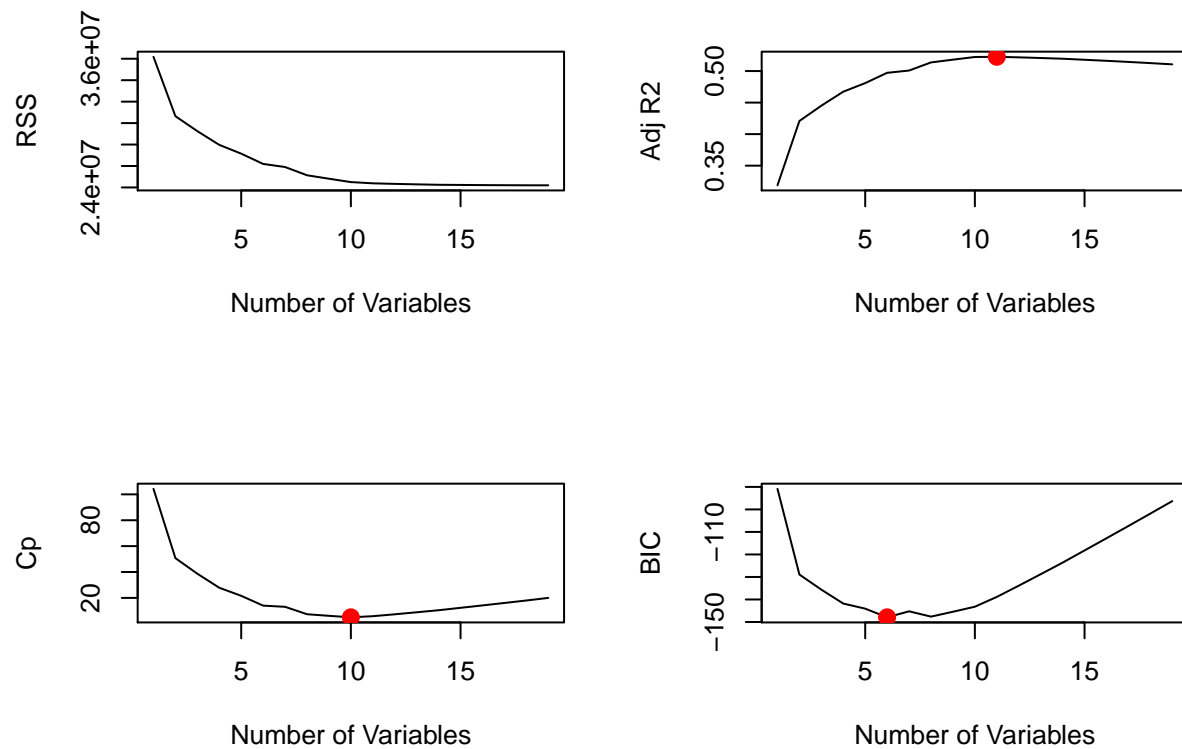
```
# Plot for easier viewing
par (mfrow = c(2, 2))
```

```
plot (reg.summary$rss, xlab = "Number of Variables", ylab = "RSS", type = "l")
```

```
plot (reg.summary$adjr2, xlab = "Number of Variables", ylab = "Adj R2", type = "l")
idx <- which.max(reg.summary$adjr2)
points(idx, reg.summary$adjr2[idx], col="red", cex=2, pch=20)
```

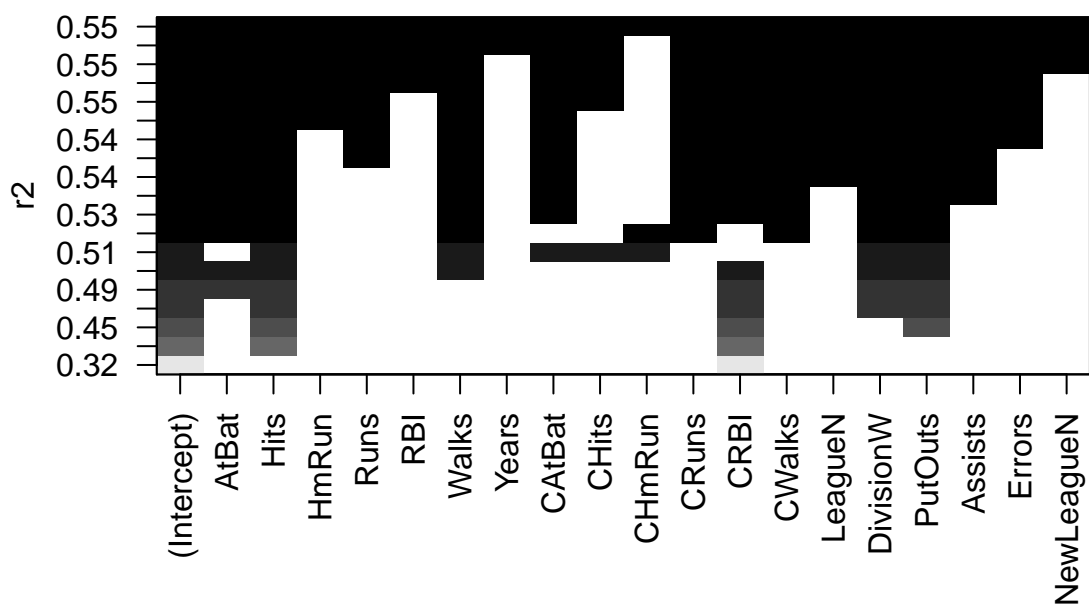
```
plot (reg.summary$cp, xlab = "Number of Variables", ylab = "Cp", type = "l")
idx <- which.min(reg.summary$cp)
points(idx, reg.summary$cp[idx], col="red", cex=2, pch=20)
```

```
plot (reg.summary$bic, xlab = "Number of Variables", ylab = "BIC", type = "l")
idx <- which.min(reg.summary$bic)
points (idx, reg.summary$bic[idx], col="red", cex=2, pch=20)
```

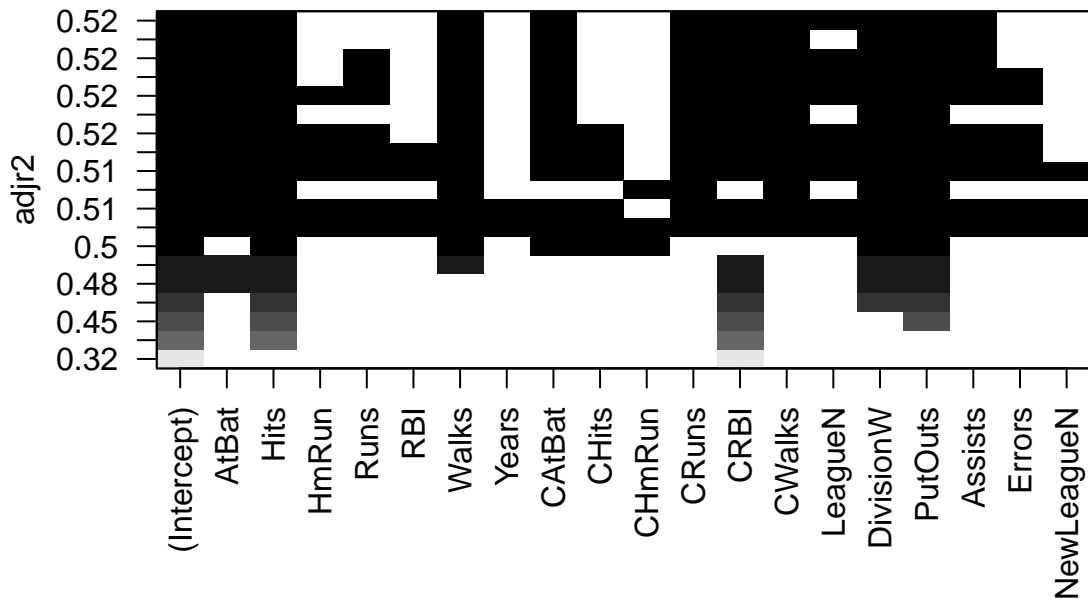


The `regsubsets()` function has a built-in `plot()` command which can be used to display the selected variables for the best model with a given number of predictors, ranked according to the BIC, Cp, adjusted R2, or AIC. **Black square** for each variable selected according to the optimal model associated with that statistic.

```
plot(regfit.full, scale = "r2")
```



```
plot(regfit.full, scale = "adjr2")
```



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

Coefficients for model with best fit

```
coef(regfit.full, 10)          #based on Adj R2 and Cp
```

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

```
coef(regfit.full, 6)          #based on BIC
```

```
## (Intercept)      AtBat      Hits      Walks      CRBI      DivisionW
##  91.5117981   -1.8685892    7.6043976    3.6976468    0.6430169  -122.9515338
##      PutOuts
##    0.2643076
```

```
# Fitting the Final Regression Model on full data
```

```
summary(lm(Salary~AtBat +Hits +Walks +CRBI +Division +PutOuts +CAtBat +CRuns
            +CWalks +Assists, d_Hitters))
```

```
##
## Call:
## lm(formula = Salary ~ AtBat + Hits + Walks + CRBI + Division +
##     PutOuts + CAtBat + CRuns + CWalks + Assists, data = d_Hitters)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -939.11 -176.87  -34.08   130.90  1910.55
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  162.53544   66.90784   2.429 0.015830 *
## AtBat        -2.16865    0.53630  -4.044 7.00e-05 ***
## Hits         6.91802    1.64665   4.201 3.69e-05 ***
## Walks        5.77322    1.58483   3.643 0.000327 ***
## CRBI         0.77431    0.20961   3.694 0.000271 ***
## DivisionW   -112.38006   39.21438  -2.866 0.004511 **
## PutOuts      0.29737    0.07444   3.995 8.50e-05 ***
## CAtBat      -0.13008    0.05550  -2.344 0.019858 *
## CRuns        1.40825    0.39040   3.607 0.000373 ***
## CWalks      -0.83083    0.26359  -3.152 0.001818 **
## Assists      0.28317    0.15766   1.796 0.073673 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 311.8 on 252 degrees of freedom
## Multiple R-squared:  0.5405, Adjusted R-squared:  0.5223
## F-statistic: 29.64 on 10 and 252 DF,  p-value: < 2.2e-16
```

```
summary(lm(Salary~AtBat +Hits +Walks +CRBI +Division +PutOuts, d_Hitters))
```

```
##
## Call:
## lm(formula = Salary ~ AtBat + Hits + Walks + CRBI + Division +
##     PutOuts, data = d_Hitters)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -873.11 -181.72  -25.91   141.77  2040.47
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   91.51180   65.00006   1.408 0.160382
## AtBat        -1.86859    0.52742  -3.543 0.000470 ***
## Hits         7.60440    1.66254   4.574 7.46e-06 ***
## Walks        3.69765    1.21036   3.055 0.002488 **
## CRBI         0.64302    0.06443   9.979 < 2e-16 ***
## DivisionW   -122.95153   39.82029  -3.088 0.002239 **
## PutOuts      0.26431    0.07477   3.535 0.000484 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 319.9 on 256 degrees of freedom
## Multiple R-squared:  0.5087, Adjusted R-squared:  0.4972
```



```
## F-statistic: 44.18 on 6 and 256 DF, p-value: < 2.2e-16
```

Forward & Backward Selection

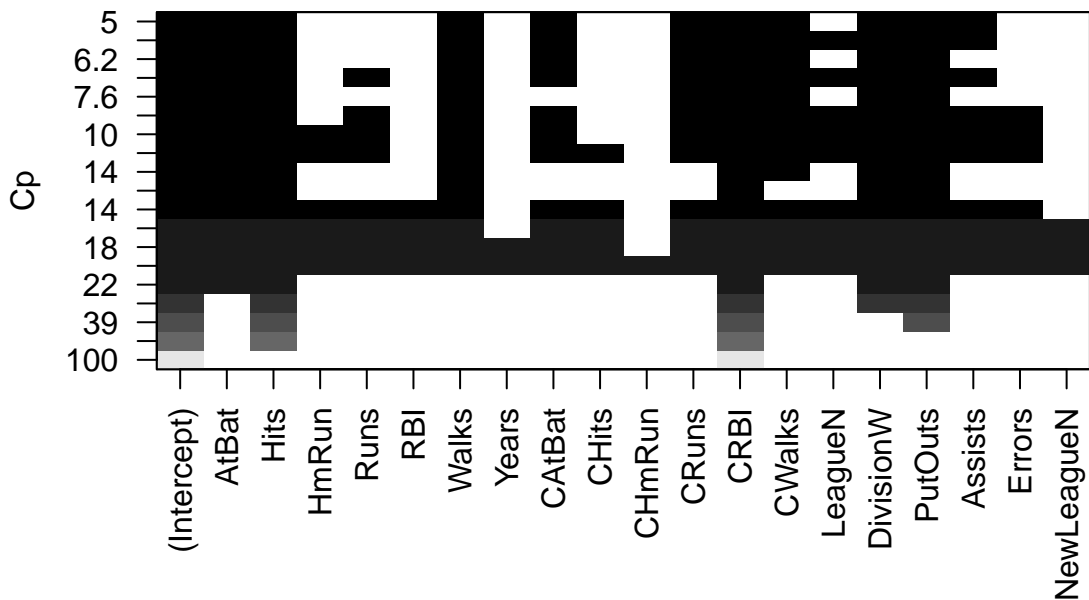
```
#Forward
```

```
regfit.fwd <- regsubsets(Salary ~., d_Hitters, nvmax=dim(d_Hitters)-1, method="forward")
summary(regfit.fwd)
```

```
## Subset selection object
## Call: regsubsets.formula(Salary ~ ., d_Hitters, nvmax = dim(d_Hitters) -
##      1, 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 CRBI
## 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 ) "*" "*" "*" "*" "*" "*" "*" "*" "*" "*" "*" "*"
##
##      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")
```



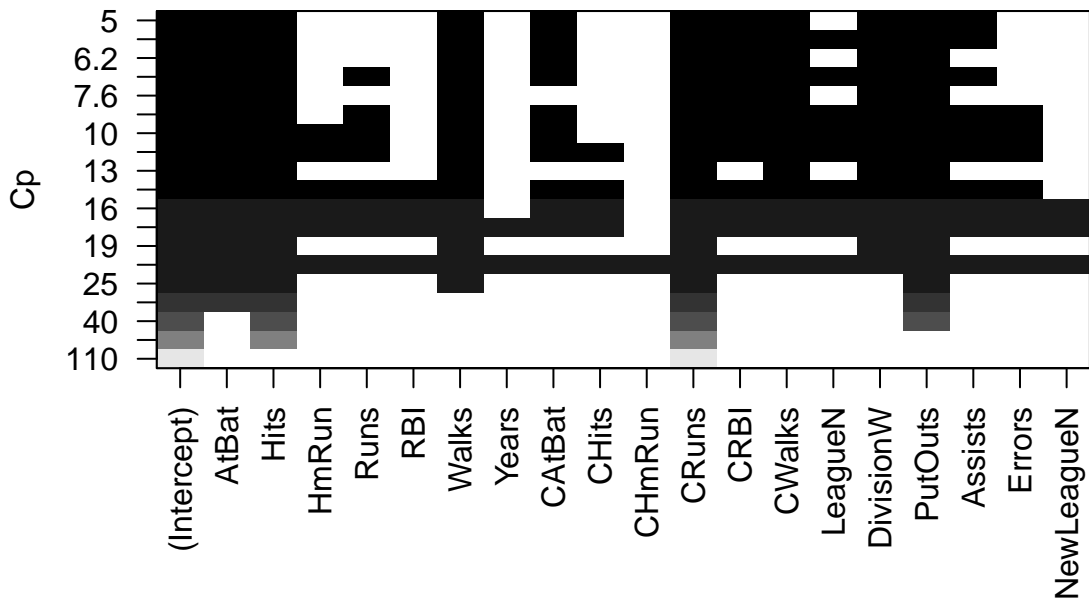
```
#Backward
regfit.back <- regsubsets(Salary ~., d_Hitters, nvmax=dim(d_Hitters)-1, method="backward")
summary(regfit.back)
```

```
## Subset selection object
## Call: regsubsets.formula(Salary ~ ., d_Hitters, nvmax = dim(d_Hitters) -
##      1, method = "backward")
## 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: backward
##      AtBat Hits HmRun Runs RBI Walks Years CAtBat CHits CHmRun CRuns CRBI
## 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 ) "*" "*" "*" "*" "*" "*" "*" "*" "*" "*" " " " " "*" "*"
##      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.back, scale = "Cp")
```



```
#Comparing 7 variable models from two approaches
coef(regfit.full, 7)
```

```
## (Intercept)      Hits      Walks      CAtBat      CHits      CHmRun
## 79.4509472    1.2833513    3.2274264   -0.3752350    1.4957073    1.4420538

```

```
## DivisionW PutOuts
## -129.9866432 0.2366813
```

```
coef(regfit.fwd, 7)
```

```
## (Intercept) AtBat Hits Walks CRBI CWalks
## 109.7873062 -1.9588851 7.4498772 4.9131401 0.8537622 -0.3053070
## DivisionW PutOuts
## -127.1223928 0.2533404
```

```
coef(regfit.back, 7)
```

```
## (Intercept) AtBat Hits Walks CRuns CWalks
## 105.6487488 -1.9762838 6.7574914 6.0558691 1.1293095 -0.7163346
## DivisionW PutOuts
## -116.1692169 0.3028847
```

Choosing among models using Train & Validation set method

Model.matrix() function is used in many regression packages to build an “X” matrix from data.

```
set.seed(1)
```

```
dim(d_Hitters)
```

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

```
train = sample(seq(263),180, replace = FALSE) #2/3rd training
regfit.train.fwd <- regsubsets(Salary ~., d_Hitters[train,], nvmax=dim(d_Hitters)-1, method="forward")
```

```
RMSE = rep(NA, 19)
```

```
x.test = model.matrix(Salary ~., d_Hitters[-train,])
```

```
# regsubset does not have a 'Predict' function, so developing our own
```

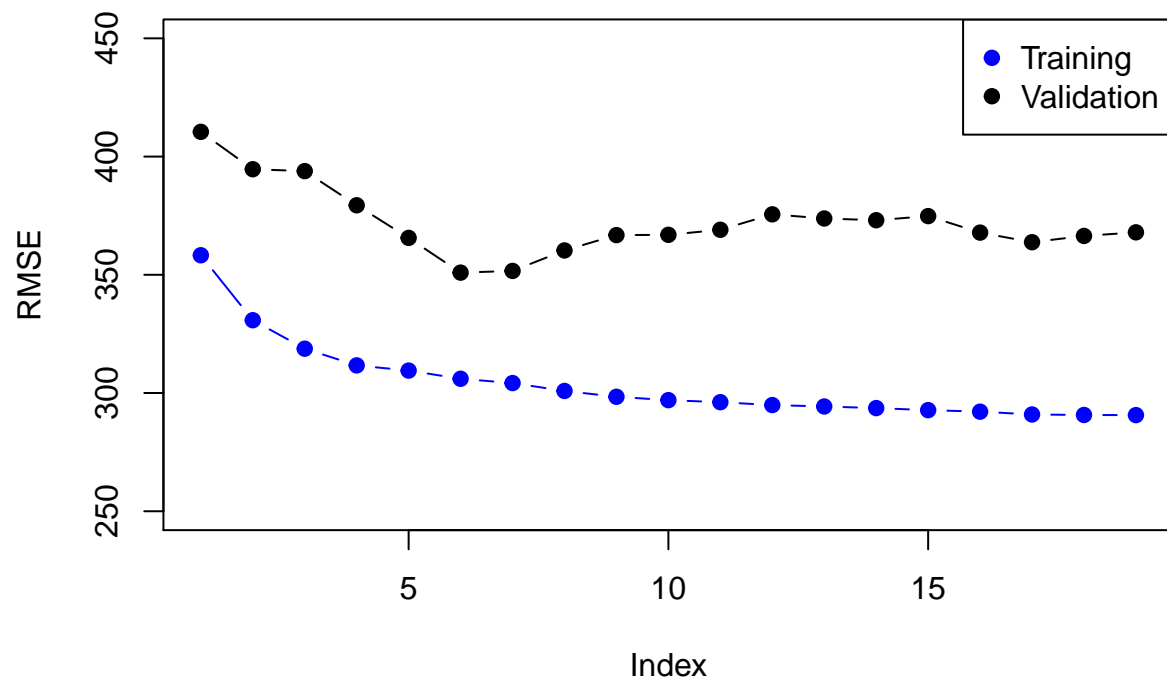
```
for (i in 1:19){
  coefi = coef(regfit.train.fwd, id=i)
  predi = x.test[,names(coefi)]%*%coefi
  RMSE[i] = sqrt(mean( (d_Hitters$Salary[-train]-predi)^2 ))
}
```

```
#Model with 6 variables has lowest Test Error
```

```
plot(RMSE, ylab="RMSE", ylim=c(250,450),pch=19, type="b")
```

```
points(sqrt(regfit.train.fwd$rss[-1]/180), col="blue", pch=19, type="b")
```

```
legend("topright", legend=c("Training", "Validation"), col=c("blue", "black"), pch=19)
```



Writing a Predict function for future use, since regsubsets doesn't work with generic predict function:

```
print(regfit.train.fwd$call[[2]])
```

```
## Salary ~ .
```

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

Choosing among models using Cross Validation method

```
set.seed(11)

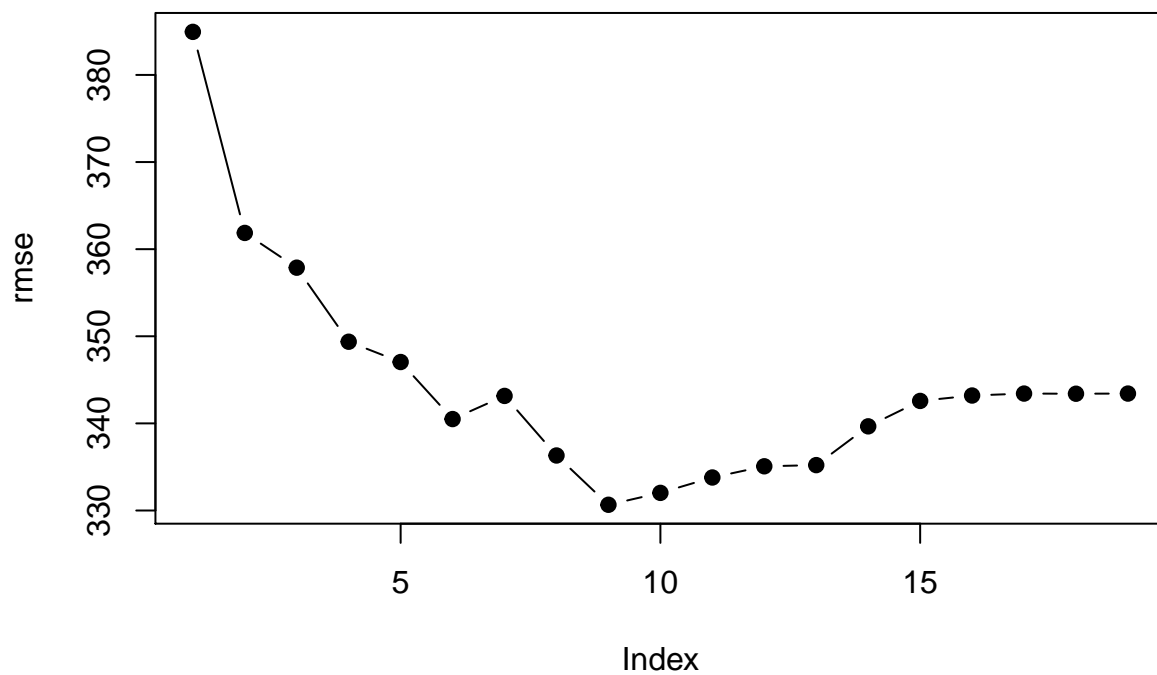
#Assign each row to a fold ranging from 1 to 10
folds = sample(rep(1:10, length=nrow(d_Hitters)))
table(folds)
```

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

#Initialize empty error matrix
cv.errors = matrix(NA, 10, 19) #10 folds, 19 variables

for(k in 1:10){
  cv_fit_k = regsubsets(Salary~., d_Hitters[folds!=k,], nvmax=19, method="forward")
  for(i in 1:19){
    pred_ki = predict(cv_fit_k, d_Hitters[folds==k,], id=i)
    cv.errors[k,i] = mean((d_Hitters$Salary[folds==k]-pred_ki)^2)
  }
}

#Average error
rmse = sqrt( apply(cv.errors, 2, mean))
plot(rmse, pch=19, type="b")
```



```
#Cross Validation approach select a 9-variable model.
#Perform best subset selection on full data set.
which.min(rmse)
```

```
## [1] 9
```

```
coef( regsubsets(Salary~., data=d_Hitters, nvmax=19), 9)
```

##	(Intercept)	AtBat	Hits	Walks	CAtBat
##	146.24960033	-1.93676754	6.65672102	5.55204413	-0.09953904
##	CRuns	CRBI	CWalks	DivisionW	PutOuts
##	1.25067124	0.66176849	-0.77798498	-115.34950146	0.27773062

Shrinkage: Ridge and Lasso

This function has a different syntax from other model-fitting functions. In particular, we must pass in an x matrix as well as a y vector.

Argument **alpha** determines the model type. The penalty is defined as $(1 - \alpha)/2||\beta||_2^2 + \alpha||\beta||_1$ where $0 \leq \alpha \leq 1$.

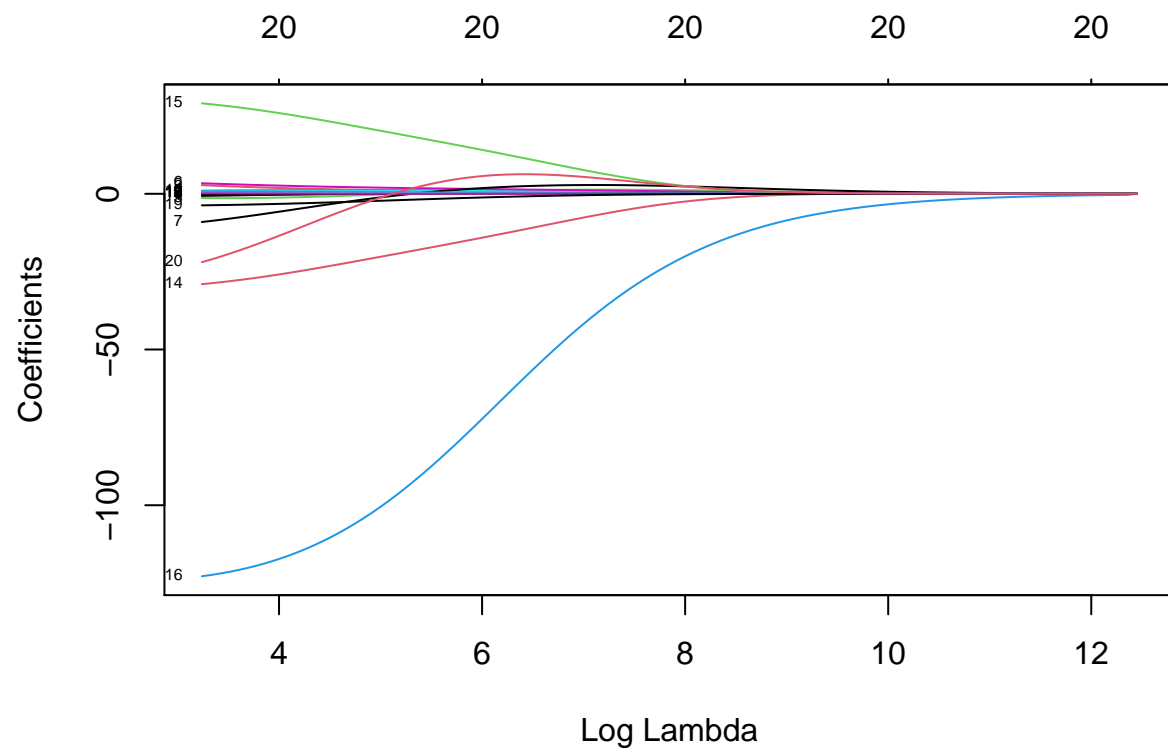
Therefore, **alpha=1 is the lasso penalty, and alpha=0 the ridge penalty**. For alpha between 0 and 1, we get elastic-net.

Note that by default, the glmnet() function standardizes the variables so that they are on the same scale. To turn off this default setting, use the argument standardize = FALSE.

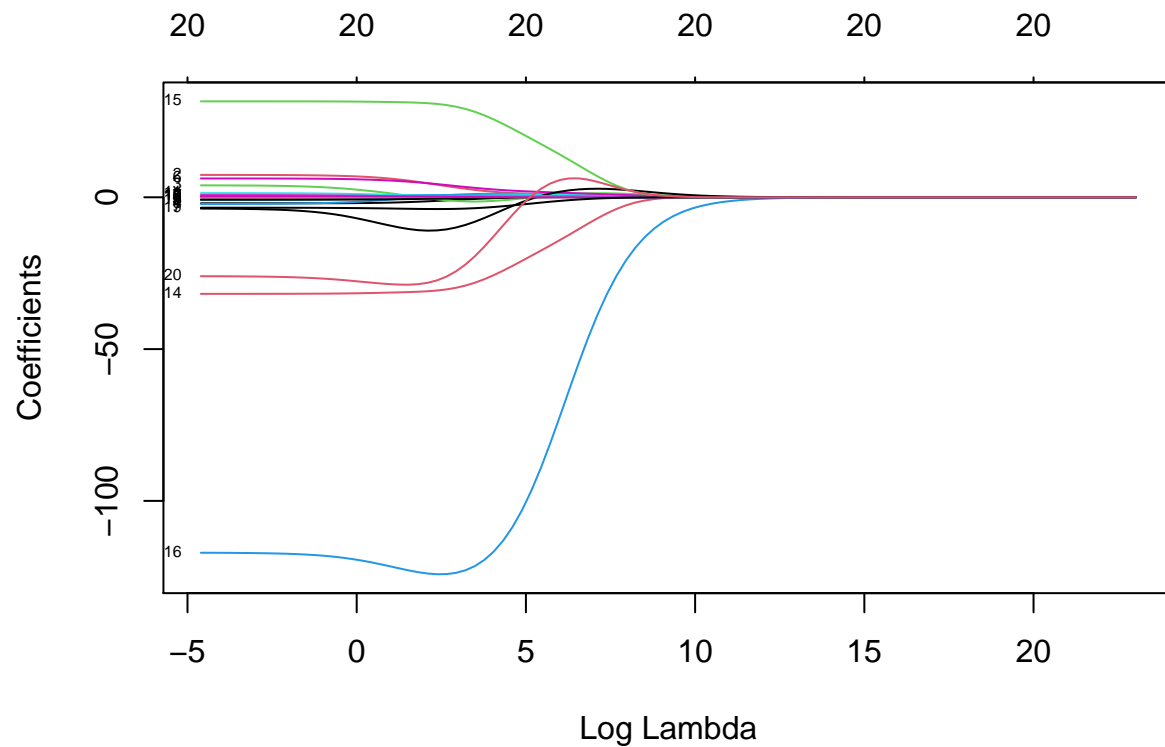
Ridge Penalty - no feature selection

```
# Ridge penalty
x = model.matrix(Salary~.-1, data=d_Hitters) #dropping the intercept
y = d_Hitters$Salary

# Fit with default lambda grid
fit.ridge = glmnet(x,y,alpha=0)
plot(fit.ridge, xvar="lambda", label=TRUE)
```

```
# User-defined lambda grid
grid = 10^seq(10,-2,length=100)
ridge.mod <- glmnet (x, y, alpha = 0, lambda = grid)
plot(ridge.mod, xvar="lambda", label=TRUE)
```



```
# Checking Coefficients for different lambdas
ridge.mod$lambda[50]
```

```
## [1] 11497.57
```

```
coef(ridge.mod)[,50]
```

```
##      (Intercept)      AtBat      Hits      HmRun      Runs
## 407.399396904    0.036958511    0.138184676    0.524663826    0.230712132
##           RBI      Walks      Years      CAtBat      CHits
##  0.239850635    0.289621892    1.107710345    0.003131822    0.011653657
##      CHmRun      CRuns      CRBI      CWalks      LeagueA
##  0.087547281    0.023380056    0.024138479    0.025015505   -0.082038139
##      LeagueN      DivisionW      PutOuts      Assists      Errors
##  0.082040144   -6.215425597    0.016482325    0.002612463   -0.020523535
##      NewLeagueN
##  0.298876792
```

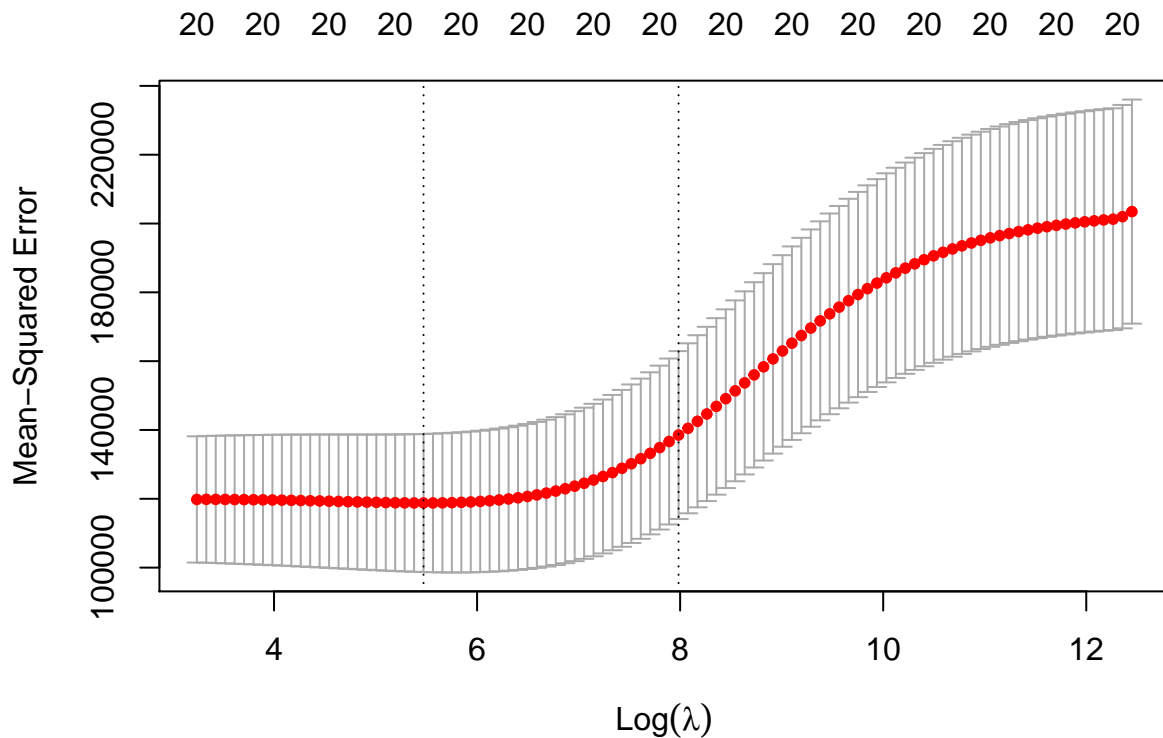
```
ridge.mod$lambda[60]
```

```
## [1] 705.4802
```

```
coef(ridge.mod)[,60]
```

```
## (Intercept)      AtBat      Hits      HmRun      Runs      RBI
## 61.72599501  0.11266871  0.65790290  1.19513175  0.94289598  0.85041323
##      Walks      Years      CAtBat      CHits      CHmRun      CRuns
## 1.31891024  2.60105804  0.01082533  0.04671252  0.33835636  0.09359447
##      CRBI      CWalks      LeagueA      LeagueN      DivisionW      PutOuts
## 0.09777821  0.07182962 -10.49032970  10.48716517 -54.62727686  0.11823107
##      Assists      Errors      NewLeagueN
## 0.01577698 -0.72133826  6.22986245
```

```
# In-build Cross Validation (k=10 by default)
cv.ridge = cv.glmnet(x,y,alpha=0)
plot(cv.ridge)      #two dashed lines
```



Review best fit values of **lambda** λ_{\min} = value of lambda that gives minimum cvm (mean cross-validated error). λ_{1se} = largest value of lambda st. error is within 1 std error of the min.

```
# Extract best value for lambda based on CV
cv.ridge$lambda.min
```

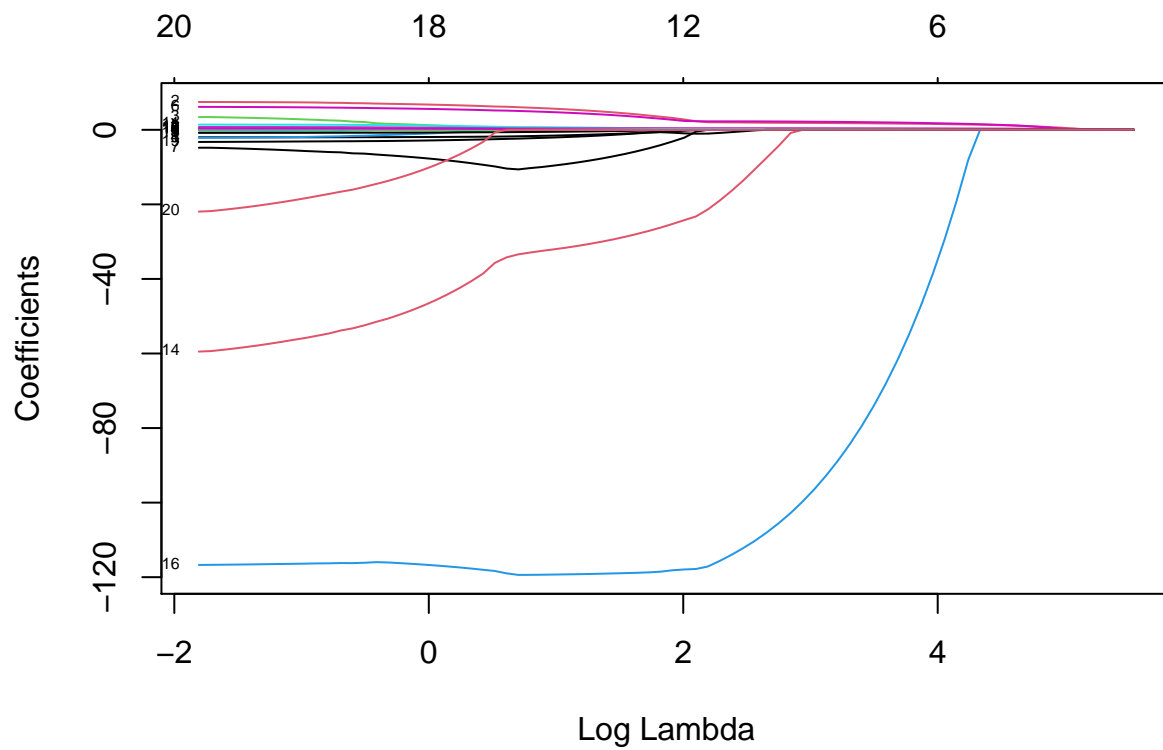
```
## [1] 238.0769
```

```
cv.ridge$lambda.1se
```

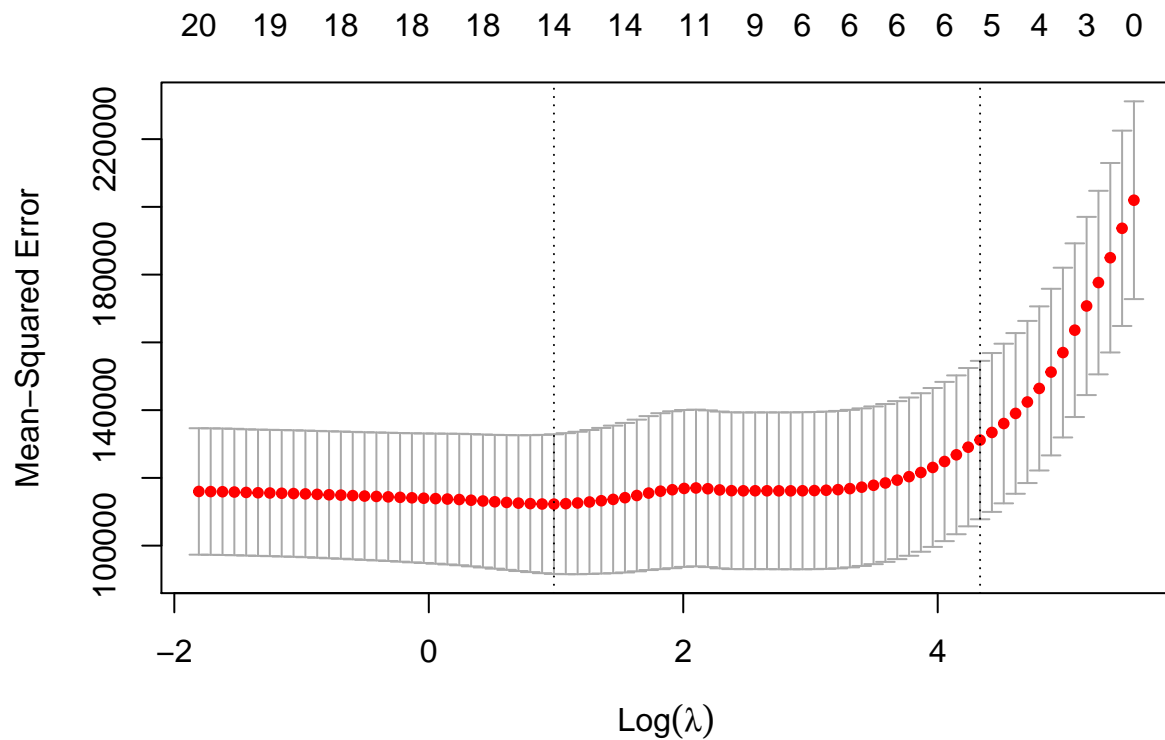
```
## [1] 2935.124
```

Lasso Penalty - shrinkage + feature selection

```
# Lasso penalty  
fit.lasso = glmnet(x,y,alpha=1)  
plot(fit.lasso, xvar="lambda", label=TRUE)
```



```
# In-build Cross Validation  
cv.lasso = cv.glmnet(x,y,alpha=1)  
plot(cv.lasso)
```



```
# Extract best value for lambda based on CV
cv.lasso$lambda.min
```

```
## [1] 2.674375
```

```
cv.lasso$lambda.1se
```

```
## [1] 76.16717
```

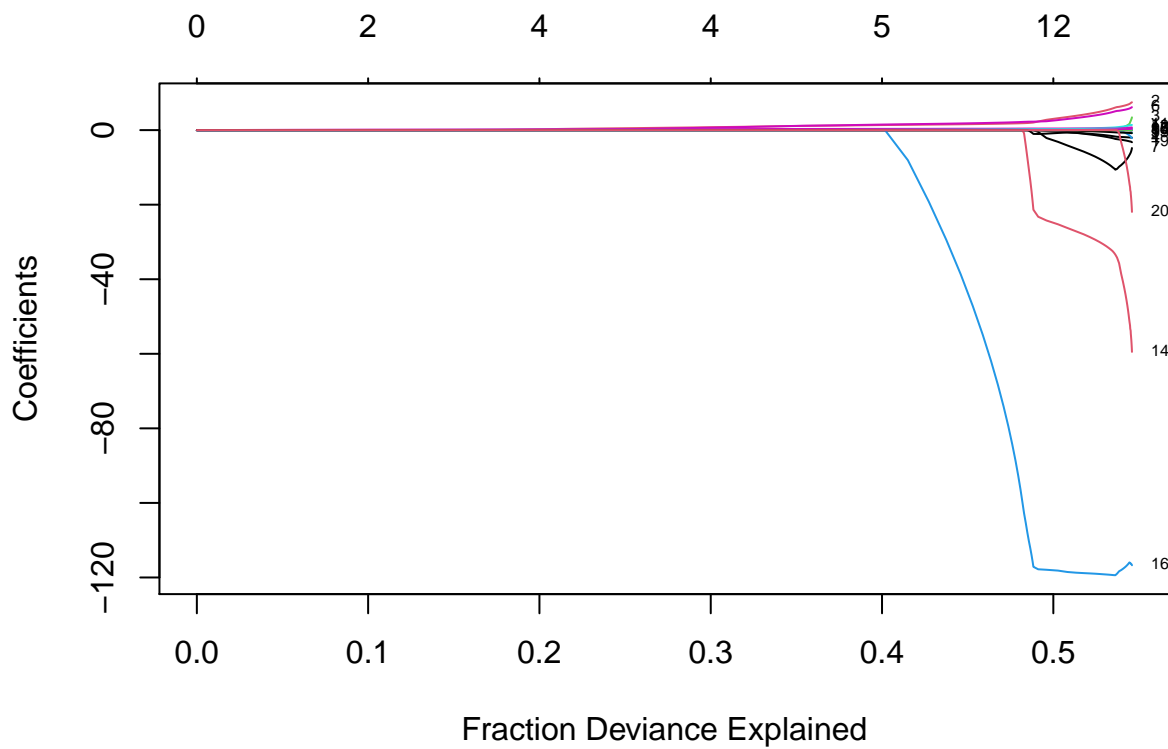
```
# Review Coeff for best fit model
coef(cv.lasso)
```

```
## 21 x 1 sparse Matrix of class "dgCMatrix"
##                               s1
## (Intercept) 144.37970485
## AtBat      .
## Hits       1.36380384
## HmRun      .
## Runs       .
## RBI        .
## Walks      1.49731098
## Years      .
## CAtBat     .
## CHits      .
```

```
## CHmRun      .
## CRuns       0.15275165
## CRBI        0.32833941
## CWalks      .
## LeagueA     .
## LeagueN     .
## DivisionW   .
## PutOuts     0.06625755
## Assists     .
## Errors      .
## NewLeagueN  .
```

The plot shows that a lot of R2 is explained by variables with heavily shrunk coefficients And at the end, only a small improvement is caused in R2 by some big increase in coefficients, *possibly implying over-fitting*.

```
plot(fit.lasso, xvar="dev", label=TRUE)
```



Using Train/ Validation split instead fo find best model.

```
# Train/ Test approach
train.lasso = glmnet(x[train,],y[train],alpha=1)
train.lasso
```

```
##
## Call:  glmnet(x = x[train, ], y = y[train], alpha = 1)
```

```

##
##      Df  %Dev  Lambda
## 1    0  0.00 262.100
## 2    1  5.92 238.800
## 3    1 10.83 217.600
## 4    1 14.91 198.300
## 5    2 19.72 180.600
## 6    3 23.94 164.600
## 7    3 27.45 150.000
## 8    3 30.37 136.700
## 9    3 32.79 124.500
## 10   3 34.80 113.500
## 11   4 36.50 103.400
## 12   5 38.77  94.190
## 13   6 40.90  85.820
## 14   6 42.73  78.200
## 15   6 44.25  71.250
## 16   6 45.51  64.920
## 17   6 46.55  59.150
## 18   6 47.42  53.900
## 19   6 48.14  49.110
## 20   6 48.74  44.750
## 21   6 49.24  40.770
## 22   6 49.65  37.150
## 23   6 49.99  33.850
## 24   7 50.28  30.840
## 25   7 50.51  28.100
## 26   8 50.71  25.610
## 27   8 50.94  23.330
## 28   8 51.12  21.260
## 29   8 51.28  19.370
## 30   8 51.41  17.650
## 31   8 51.52  16.080
## 32   8 51.60  14.650
## 33   8 51.68  13.350
## 34   9 51.75  12.170
## 35   9 51.99  11.080
## 36  10 52.23  10.100
## 37  10 52.44   9.202
## 38  11 52.64   8.385
## 39  11 52.82   7.640
## 40  11 52.97   6.961
## 41  11 53.09   6.343
## 42  11 53.19   5.779
## 43  12 53.28   5.266
## 44  14 53.53   4.798
## 45  14 53.83   4.372
## 46  15 54.06   3.984
## 47  16 54.45   3.630
## 48  16 54.79   3.307
## 49  16 55.06   3.013
## 50  16 55.29   2.746
## 51  17 55.48   2.502
## 52  17 55.65   2.280

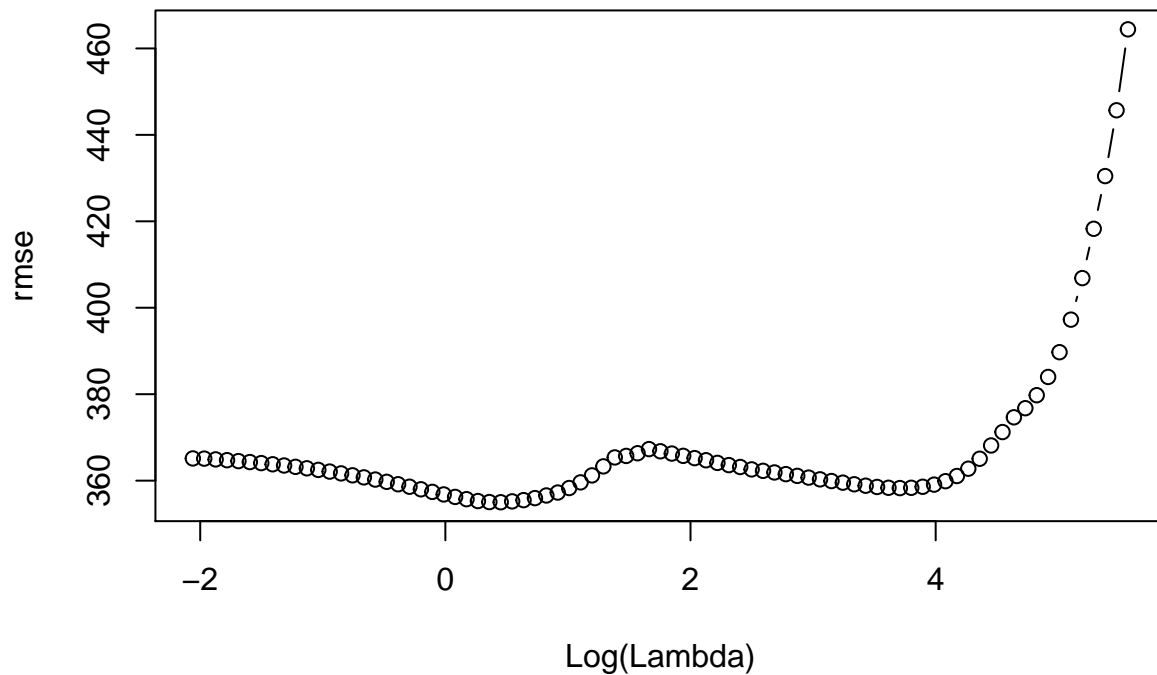
```

```
## 53 17 55.78 2.077
## 54 17 55.89 1.892
## 55 18 56.00 1.724
## 56 18 56.16 1.571
## 57 18 56.30 1.432
## 58 19 56.42 1.304
## 59 19 56.53 1.189
## 60 19 56.63 1.083
## 61 19 56.71 0.987
## 62 19 56.77 0.899
## 63 19 56.83 0.819
## 64 19 56.88 0.746
## 65 19 56.92 0.680
## 66 19 56.95 0.620
## 67 19 56.98 0.565
## 68 19 57.00 0.514
## 69 19 57.02 0.469
## 70 19 57.04 0.427
## 71 19 57.05 0.389
## 72 19 57.06 0.355
## 73 19 57.07 0.323
## 74 19 57.08 0.294
## 75 19 57.08 0.268
## 76 19 57.09 0.244
## 77 19 57.09 0.223
## 78 19 57.10 0.203
## 79 19 57.10 0.185
## 80 19 57.11 0.168
## 81 19 57.11 0.154
## 82 19 57.11 0.140
## 83 19 57.11 0.127
```

```
pred = predict(train.lasso, x[-train,])
dim(pred) #83 values of lambda and 83 rows in test data
```

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

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

```
# Best Lambda
idx = which.min(rmse)
train.lasso$lambda[idx]
```

```
## [1] 1.571184
```

Principal Components Regression (PCR)

Setting `scale = TRUE` has the effect of standardizing each predictor. Setting `validation = "CV"` causes `pcr()` to compute the ten-fold cross-validation error for each possible value of `M`, the number of principal components used.

Note that `pcr()` reports the root mean squared error.

```
set.seed(2)
pcr.fit <- pcr(Salary~., data=d_Hitters, scale=TRUE, validation="CV")
summary(pcr.fit)
```

```
## Data:      X dimension: 263 19
## Y dimension: 263 1
## Fit method: svdpc
## Number of components considered: 19
##
## VALIDATION: RMSEP
```

```
## Cross-validated using 10 random segments.
##      (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV              452    351.9   353.2   355.0   352.8   348.4   343.6
## adjCV           452    351.6   352.7   354.4   352.1   347.6   342.7
##      7 comps  8 comps  9 comps 10 comps 11 comps 12 comps 13 comps
## CV       345.5   347.7   349.6   351.4   352.1   353.5   358.2
## adjCV     344.7   346.7   348.5   350.1   350.7   352.0   356.5
##      14 comps 15 comps 16 comps 17 comps 18 comps 19 comps
## CV       349.7   349.4   339.9   341.6   339.2   339.6
## adjCV     348.0   347.7   338.2   339.7   337.2   337.6
##
## TRAINING: % variance explained
##      1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps  8 comps
## X          38.31   60.16   70.84   79.03   84.29   88.63   92.26   94.96
## Salary     40.63   41.58   42.17   43.22   44.90   46.48   46.69   46.75
##      9 comps 10 comps 11 comps 12 comps 13 comps 14 comps 15 comps
## X          96.28   97.26   97.98   98.65   99.15   99.47   99.75
## Salary     46.86   47.76   47.82   47.85   48.10   50.40   50.55
##      16 comps 17 comps 18 comps 19 comps
## X          99.89   99.97   99.99   100.00
## Salary     53.01   53.85   54.61   54.61
```

```
pcr.fit$loadings
```

```
##
## Loadings:
##      Comp 1 Comp 2 Comp 3 Comp 4 Comp 5 Comp 6 Comp 7 Comp 8 Comp 9
## AtBat      0.198  0.384
## Hits       0.196  0.377
## HmRun       0.204  0.237  0.216 -0.236
## Runs       0.198  0.378
## RBI        0.235  0.315      -0.139
## Walks      0.209  0.230      -0.131
## Years      0.283 -0.262
## CAtBat     0.330 -0.193
## CHits      0.331 -0.183
## CHmRun     0.319 -0.126
## CRuns      0.338 -0.172
## CRBI       0.340 -0.168
## CWalks     0.317 -0.192
## LeagueN    -0.548 -0.396
## DivisionW      -0.986
## PutOuts     0.156      -0.288 -0.106 -0.924
## Assists     0.169 -0.398  0.524
## Errors     0.201 -0.383  0.422      -0.148  0.373 -0.301 -0.609
## NewLeagueN  -0.545 -0.418
##      Comp 10 Comp 11 Comp 12 Comp 13 Comp 14 Comp 15 Comp 16 Comp 17
## AtBat      0.146      -0.103
## Hits       0.130      -0.121
## HmRun     -0.351 -0.202  0.315  0.109
## Runs      -0.312  0.322  0.381 -0.267  0.468  0.221 -0.141
## RBI       -0.172  0.243 -0.348 -0.440
## Walks     -0.121  0.176 -0.185
## Years     -0.513  0.192 -0.355  0.605
```

```

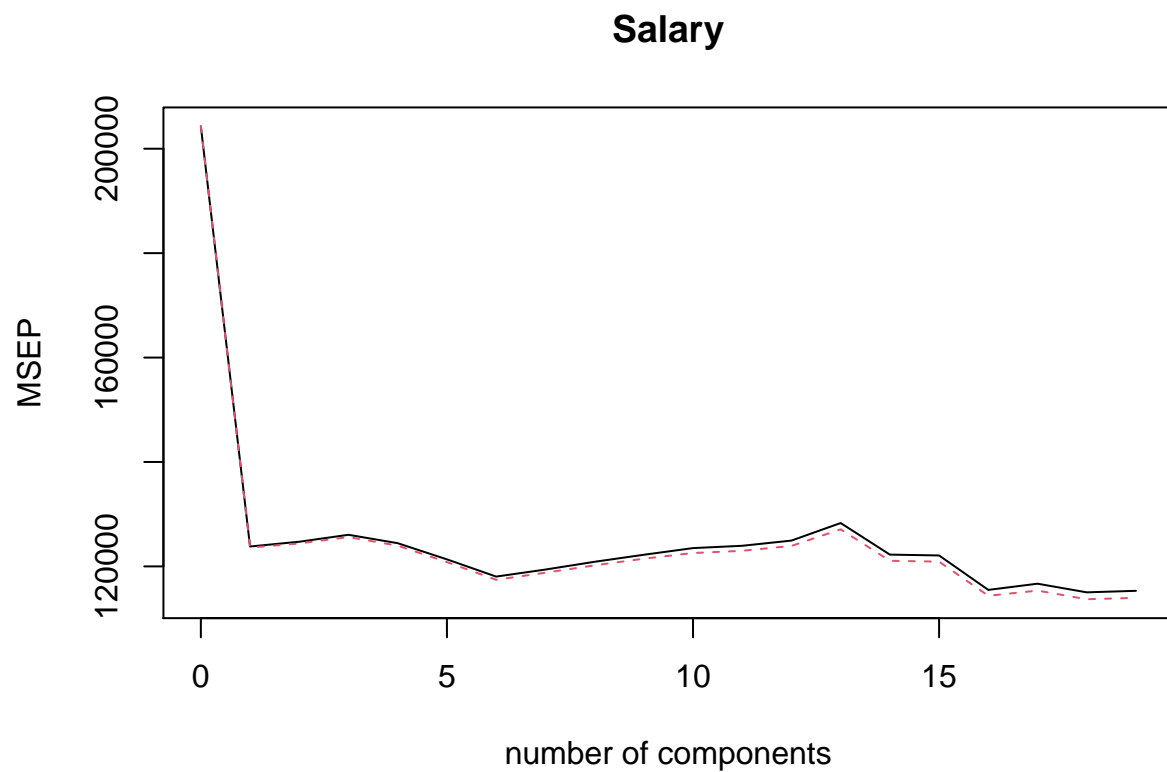
## CAtBat      -0.101          -0.149 -0.168 -0.158          -0.182
## CHits              -0.267 -0.290 -0.137 -0.110
## CHmRun      0.651          0.330          0.292
## CRuns       -0.152  0.229 -0.202 -0.129          0.162  0.623
## CRBI        0.281          -0.121 -0.209          -0.143 -0.610
## CWalks      -0.191  0.216 -0.167  0.737  0.245          -0.170
## LeagueN      -0.581 -0.407
## DivisionW
## PutOuts
## Assists
## Errors
## NewLeagueN      0.544  0.429
##           Comp 18 Comp 19
## AtBat          0.107
## Hits
## HmRun
## Runs
## RBI
## Walks
## Years
## CAtBat      -0.720 -0.409
## CHits              0.770
## CHmRun      -0.254  0.166
## CRuns       0.400 -0.344
## CRBI        0.475 -0.260
## CWalks
## LeagueN
## DivisionW
## PutOuts
## Assists
## Errors
## NewLeagueN
##
##           Comp 1 Comp 2 Comp 3 Comp 4 Comp 5 Comp 6 Comp 7 Comp 8 Comp 9
## SS loadings    1.000  1.000  1.000  1.000  1.000  1.000  1.000  1.000  1.000
## Proportion Var 0.053  0.053  0.053  0.053  0.053  0.053  0.053  0.053  0.053
## Cumulative Var 0.053  0.105  0.158  0.211  0.263  0.316  0.368  0.421  0.474
##           Comp 10 Comp 11 Comp 12 Comp 13 Comp 14 Comp 15 Comp 16 Comp 17
## SS loadings    1.000  1.000  1.000  1.000  1.000  1.000  1.000  1.000
## Proportion Var 0.053  0.053  0.053  0.053  0.053  0.053  0.053  0.053
## Cumulative Var 0.526  0.579  0.632  0.684  0.737  0.789  0.842  0.895
##           Comp 18 Comp 19
## SS loadings    1.000  1.000
## Proportion Var 0.053  0.053
## Cumulative Var 0.947  1.000

```

```

# sum(pcr.fit$loadings[,1]^2) # sum of square of coeffs for any PC adds up to one
# sum(pcr.fit$loadings[,6]^2) # sum of square of coeffs for any PC adds up to one
validationplot(pcr.fit, val.type="MSEP")

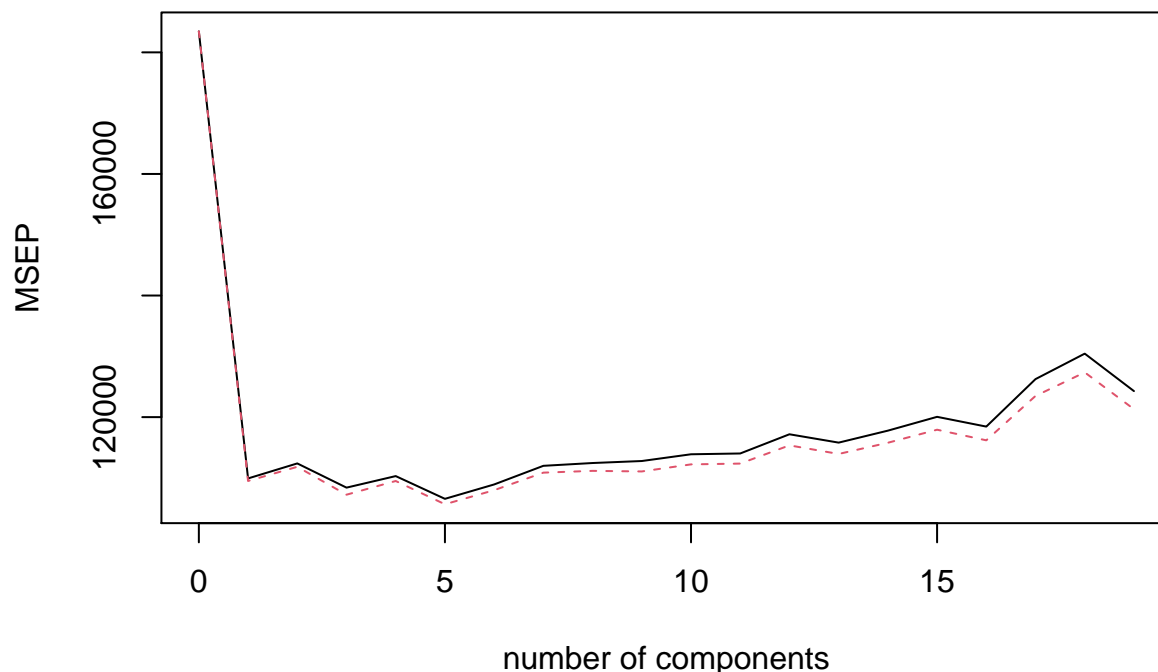
```



```
#Using Train/ Test split - 5 component model has best fit
set.seed(1)
train <- sample(1:nrow(d_Hitters), nrow(d_Hitters)/2)
x <- model.matrix(Salary ~., d_Hitters)[,-1]
y <- d_Hitters[, "Salary"]

pcr.fit.train <- pcr(Salary ~., data=d_Hitters, scale=TRUE, validation="CV",
                     subset=train) #using both training and CV!
validationplot(pcr.fit.train, val.type="MSEP")
```

Salary



```
pcr.pred <- predict(pcr.fit.train, x[-train,], ncomp=5)
mean((pcr.pred - d_Hitters[-train,"Salary"])^2)
```

```
## [1] 142811.8
```

```
#Fitting 5 component model on full-dataset
```

```
pcr.fit.5 <- pcr(Salary~., data=d_Hitters, scale=TRUE, ncomp=5)
summary(pcr.fit.5)
```

```
## Data:      X dimension: 263 19
## Y dimension: 263 1
## Fit method: svdpc
## Number of components considered: 5
## TRAINING: % variance explained
##           1 comps  2 comps  3 comps  4 comps  5 comps
## X           38.31   60.16   70.84   79.03   84.29
## Salary      40.63   41.58   42.17   43.22   44.90
```

Partial Least Square (PLS) Regression

Setting `scale = TRUE` has the effect of standardizing each predictor. Setting `validation = "CV"` causes `pcr()` to compute the ten-fold cross-validation error for each possible value of `M`, the number of principal components used.

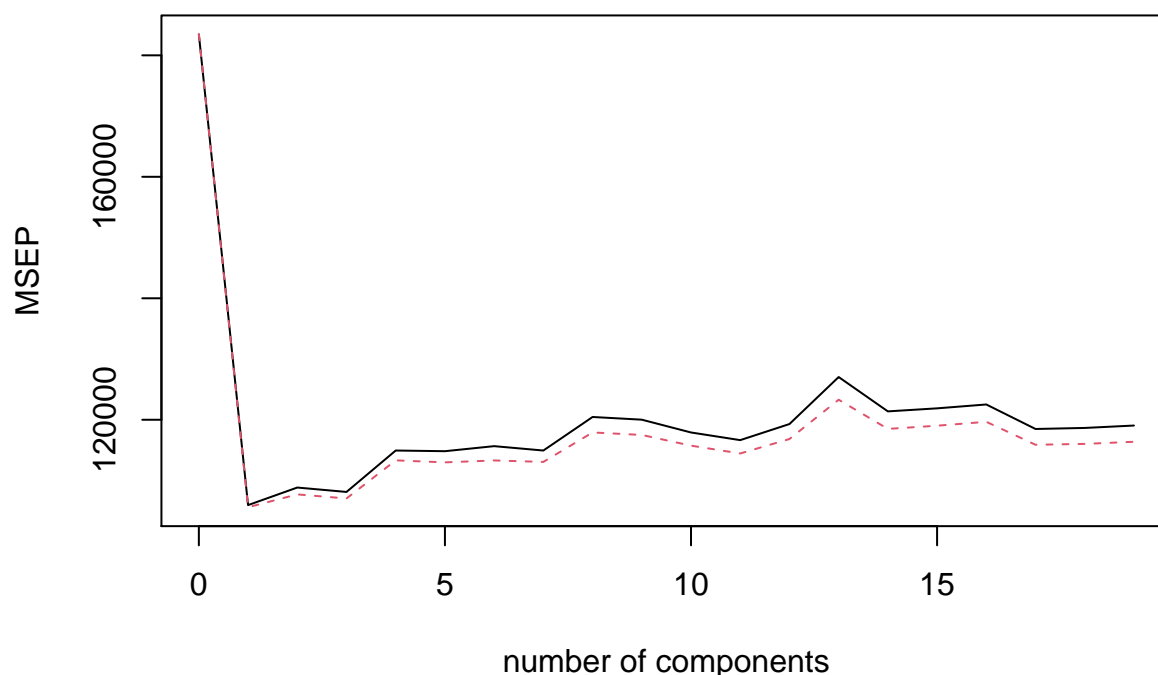
Note that `pcr()` reports the root mean squared error.

```
set.seed(1)
pls.fit <- plsr(Salary~., data=d_Hitters, subset=train, scale=TRUE, validation="CV")
summary(pls.fit)
```

```
## Data:      X dimension: 131 19
## Y dimension: 131 1
## Fit method: kernelppls
## Number of components considered: 19
##
## VALIDATION: RMSEP
## Cross-validated using 10 random segments.
##      (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV           428.3   325.5   329.9   328.8   339.0   338.9   340.1
## adjCV         428.3   325.0   328.2   327.2   336.6   336.1   336.6
##      7 comps  8 comps  9 comps 10 comps 11 comps 12 comps 13 comps
## CV           339.0   347.1   346.4   343.4   341.5   345.4   356.4
## adjCV         336.2   343.4   342.8   340.2   338.3   341.8   351.1
##      14 comps 15 comps 16 comps 17 comps 18 comps 19 comps
## CV           348.4   349.1   350.0   344.2   344.5   345.0
## adjCV         344.2   345.0   345.9   340.4   340.6   341.1
##
## TRAINING: % variance explained
##      1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps  8 comps
## X           39.13   48.80   60.09   75.07   78.58   81.12   88.21   90.71
## Salary       46.36   50.72   52.23   53.03   54.07   54.77   55.05   55.66
##      9 comps 10 comps 11 comps 12 comps 13 comps 14 comps 15 comps
## X           93.17   96.05   97.08   97.61   97.97   98.70   99.12
## Salary       55.95   56.12   56.47   56.68   57.37   57.76   58.08
##      16 comps 17 comps 18 comps 19 comps
## X           99.61   99.70   99.95  100.00
## Salary       58.17   58.49   58.56   58.62
```

```
validationplot(pls.fit, val.type="MSEP")
```

Salary



```
# Performance on Test Set
```

```
pls.pred <- predict(pls.fit, x[-train,], ncomp=1)
mean((pls.pred - d_Hitters[-train,"Salary"])^2)
```

```
## [1] 151995.3
```

```
# Performance on Full dataset
```

```
pls.fit.full <- pls(Salary~., data=d_Hitters, scale=TRUE, ncomp=1)
summary(pls.fit.full)
```

```
## Data:      X dimension: 263 19
## Y dimension: 263 1
## Fit method: kernelpls
## Number of components considered: 1
## TRAINING: % variance explained
##          1 comps
## X          38.08
## Salary     43.05
```

Notice that the percentage of variance in Salary that the one-component PLS fit explains, 43.05 %, is almost as much as that explained using the final five-component model PCR fit, 44.90 %. This is because PCR only attempts to maximize the amount of variance explained in the predictors, while PLS searches for directions that explain variance in both the predictors and the response.