statLearn R LAB.6(b) RIDGE REGRESSION AND LASSO

First, need to install and load the 'glmnet' package, glmnet does not use model formula language, so we must set up an 'x' and 'y'

```
library(ISLR)
library(glmnet)

## Warning: package 'glmnet' was built under R version 3.3.2

## Loading required package: Matrix

## Loading required package: foreach

## Loaded glmnet 2.0-10

Hitters=na.omit(Hitters)
with(Hitters,sum(is.na(Salary)))

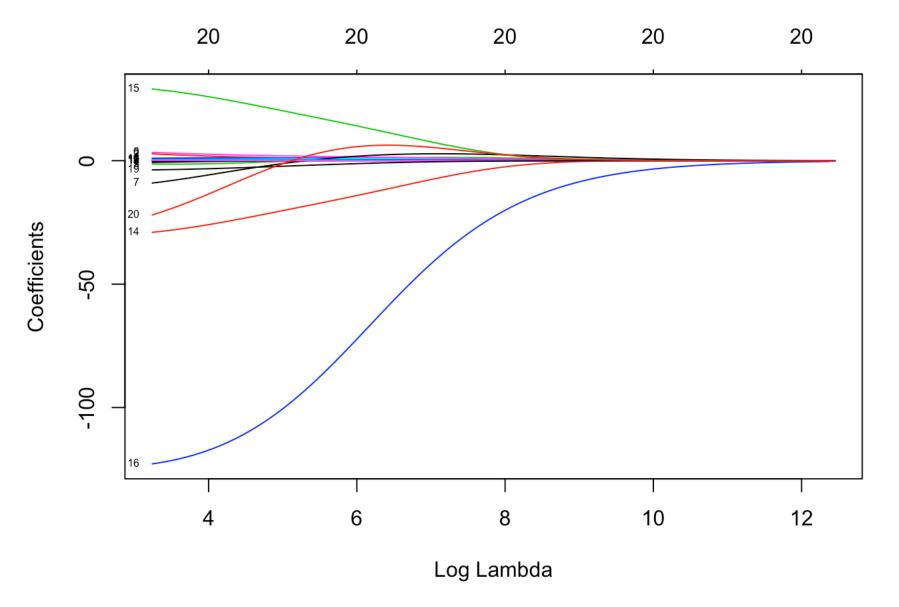
## [1] 0

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

Ridge Regression: Shrinkage of Coefficients

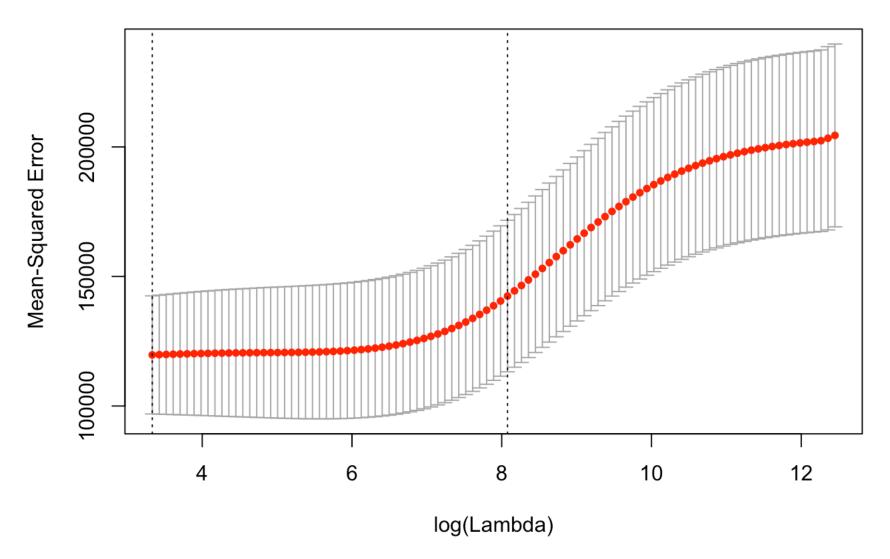
To fit Ridge-Regression model we calling 'glmnet' with 'alpha=0' (see helpfile; to fit Lasso model, alpha is set to 1). 'cv.glmnet' function will do cross-validation for us

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



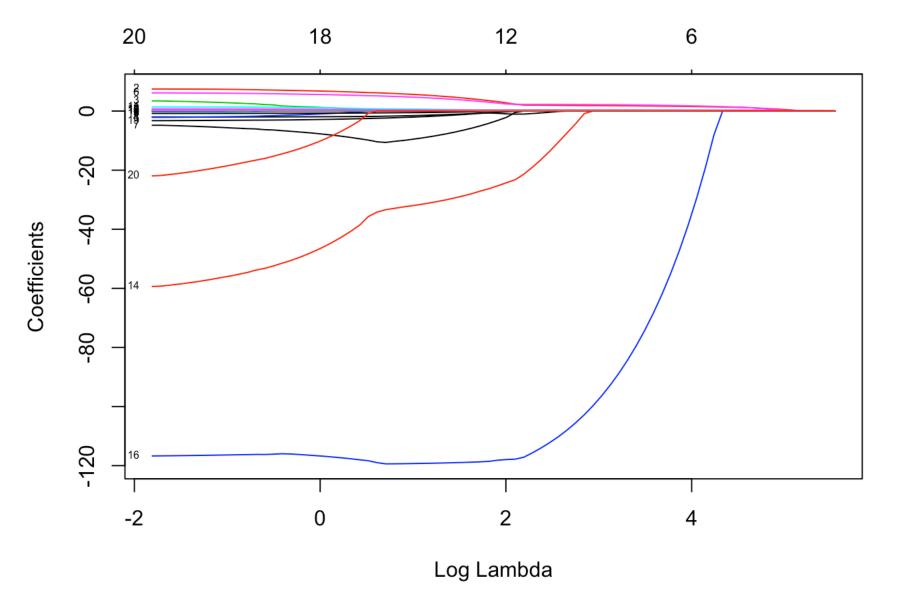
Coefficients are plotted as a function of log lambda; RR models are penalized by the SumSquares of Coefficients controlled by parameter lambda: RSS+lambda*penalty Coefficients shrink towards zero, as lambda increases

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

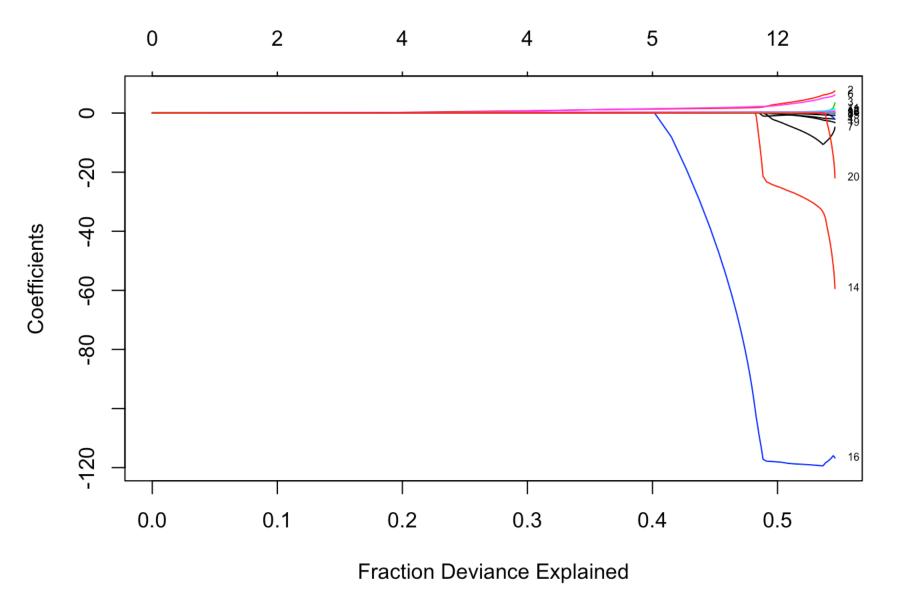


The Lasso: does Shrinkage and Variable Selection Now, we fit lasso model; using the default 'alpha=1' Lasso is similar to RR, but has slightly different penalty uses absolute value of coefficiebts, shrinking some to zero

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



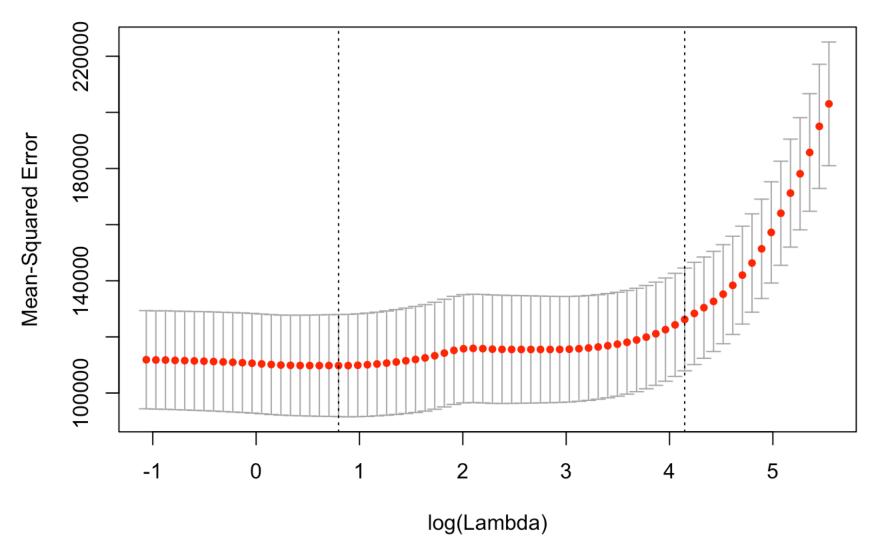
plot(fit.lasso, xvar="dev", label=TRUE)



Plot shows that initially all features are included, and then as lambda increases, only a few features are retained and the coefficients for unrelated features move to zero Plot xvar="dev" shows R^2

Use Cross-Validation to get MSE Estimates for lasso model

```
cv.lasso = cv.glmnet(x, y, alpha=1)
plot(cv.lasso)
```



coef(cv.lasso)

```
## 21 x 1 sparse Matrix of class "dgCMatrix"
##
## (Intercept) 115.3773590
## AtBat
## Hits
                  1.4753071
## HmRun
## Runs
## RBI
## Walks
                  1.6566947
## Years
## CAtBat
## CHits
## CHmRun
## CRuns
                  0.1660465
## CRBI
                  0.3453397
## CWalks
## LeagueA
## LeagueN
## DivisionW
               -19.2435216
## PutOuts
                  0.1000068
## Assists
## Errors
## NewLeagueN
```

Use earlier TRAIN/VALIDATION to select 'lambda' for the lasso: It tries to fit 100 values of lambda, and if nothing changes, then it stops. Use best lambda and fit to whole data set

```
set.seed(1)
train = sample(seq(263), 180, replace=FALSE)
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
          4 0.35920 88.56000
## [12,]
## [13,]
          5 0.37360 80.69000
```

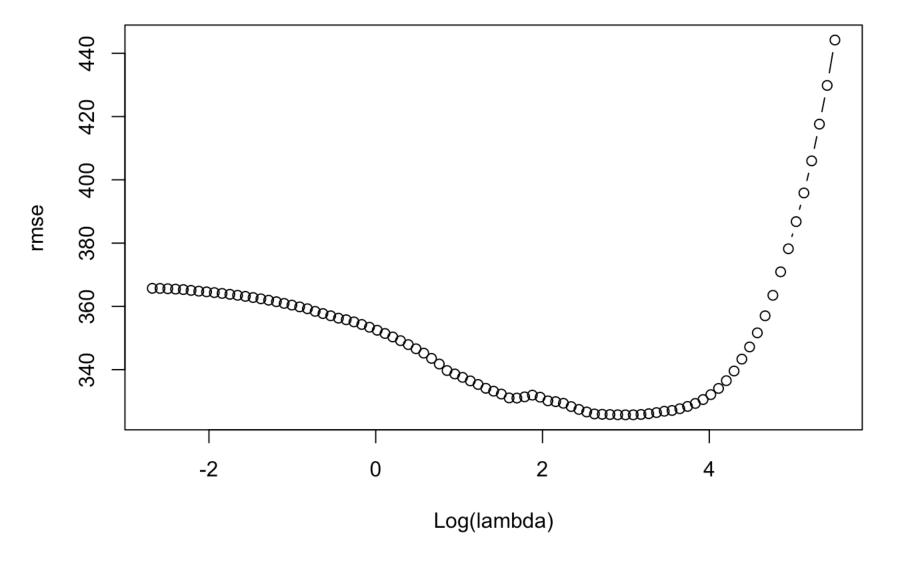
```
## [14,]
          5 0.38900
                      73.52000
## [15,]
          5 0.40190
                      66.99000
## [16,]
          5 0.41260
                      61.04000
## [17,]
          5 0.42140
                      55.62000
## [18,]
          5 0.42880
                      50.67000
                      46.17000
## [19,]
          5 0.43490
## [20,]
          5 0.43990
                      42.07000
                      38.33000
## [21,]
          5 0.44410
## [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
                      16.59000
## [30,]
          8 0.46630
## [31,]
          8 0.46730
                      15.12000
## [32,]
          8 0.46810
                      13.78000
          9 0.47110
                      12.55000
## [33,]
## [34,]
          9 0.47380
                      11.44000
          9 0.47620
                      10.42000
## [35,]
## [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
                       4.51100
## [44,] 13 0.51850
## [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"
##
## (Intercept) 107.9416686
## AtBat
## Hits 0.1591252
## HmRun
## Runs
             1.7340039
## RBI
## Walks 3.4657091
## Years
## CAtBat
## CHits
## CHmRun
            0.5386855
## CRuns
## CRBI
## CWalks
## LeagueA -30.0493021
## LeagueN
## DivisionW -113.8317016
## PutOuts 0.2915409
## Assists
## Errors
## NewLeagueN 2.0367518
```
