R Lab 6

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Section 6.5.2 (Ridge)

We use the **glmnet** library to fit LASSO and Ridge models

```
library(ISLR2)
```

```
## Warning: package 'ISLR2' was built under R version 4.4.3
```

```
library(glmnet)
```

```
## Warning: package 'glmnet' was built under R version 4.4.3

## Loading required package: Matrix

## Loaded glmnet 4.1-8
```

```
Hitters <- na.omit(Hitters)

# Here model.matrix produces a matrix corresponding to all 19 predictors and
# transforms qualitative predictors into dummies.
x <- model.matrix(Salary ~ ., Hitters)[,-1]
y <- Hitters$Salary
nrow(x)
```

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

```
length(y)
```

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

```
# Ridge Model
# NOTE: alpha=0 is ridge, alpha=1 is LASSO
grid <- 10^seq(10,-2, length = 100)
# Here, we use a grid of values for lambda from 10^10 down to 10^-2
ridge.mod <-glmnet(x, y, alpha = 0, lambda = grid) #glmnet also auto standardizes

# Dimension of coefficient matrix
dim(coef(ridge.mod))
```

```
## [1]  20 100
```

```r
# Here, lambda=11498, so the coefficients become pretty small
ridge.mod$lambda[50] # Middle lambda val
```

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

```r
coef(ridge.mod)[, 50] # Corresponding coefs for ridge model
```

```
##   (Intercept)         AtBat          Hits         HmRun          Runs
## 407.356050200   0.036957182   0.138180344   0.524629976   0.230701523
##           RBI         Walks         Years        CAtBat         CHits
##   0.239841459   0.289618741   1.107702929   0.003131815   0.011653637
##        CHmRun         CRuns          CRBI        CWalks       LeagueN
##   0.087545670   0.023379882   0.024138320   0.025015421   0.085028114
##     DivisionW       PutOuts       Assists        Errors    NewLeagueN
##  -6.215440973   0.016482577   0.002612988  -0.020502690   0.301433531
```

```r
sqrt(sum(coef(ridge.mod)[-1, 50]^2))
```

```
## [1] 6.360612
```

```r
# For lambda=705
ridge.mod$lambda[60]
```

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

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

```
##  (Intercept)        AtBat         Hits        HmRun         Runs          RBI
##  54.32519950   0.11211115   0.65622409   1.17980910   0.93769713   0.84718546
##        Walks        Years       CAtBat        CHits       CHmRun        CRuns
##   1.31987948   2.59640425   0.01083413   0.04674557   0.33777318   0.09355528
##         CRBI       CWalks      LeagueN    DivisionW      PutOuts      Assists
##   0.09780402   0.07189612  13.68370191 -54.65877750   0.11852289   0.01606037
##       Errors   NewLeagueN
##  -0.70358655   8.61181213
```

```r
sqrt(sum(coef(ridge.mod)[-1, 60]^2)) # Norm is much larger for this lambda
```

```
## [1] 57.11001
```

```r
# Use predict to obtain coefficients for fixed beta
predict(ridge.mod, s = 50, type = "coefficients")[1:20, ]
```

```
##   (Intercept)         AtBat          Hits         HmRun          Runs
##  4.876610e+01 -3.580999e-01  1.969359e+00 -1.278248e+00  1.145892e+00
##           RBI         Walks         Years        CAtBat         CHits
##  8.038292e-01  2.716186e+00 -6.218319e+00  5.447837e-03  1.064895e-01
##        CHmRun         CRuns          CRBI        CWalks       LeagueN
##  6.244860e-01  2.214985e-01  2.186914e-01 -1.500245e-01  4.592589e+01
##     DivisionW       PutOuts       Assists        Errors    NewLeagueN
## -1.182011e+02  2.502322e-01  1.215665e-01 -3.278600e+00 -9.496680e+00
```

```r
# Splitting training/testing data
set.seed(1)
train <-sample(1:nrow(x), nrow(x) / 2)
test <- (-train)
y.test <- y[test]

# Evaluating on training data
ridge.mod <-glmnet(x[train, ], y[train], alpha = 0,
 lambda = grid, thresh = 1e-12)
ridge.pred <-predict(ridge.mod, s = 4, newx = x[test, ]) # Use newx to predict on test set (and lambda=
mean((ridge.pred- y.test)^2) # MSE
```

```
## [1] 142199.2
```

```r
# MSE for intercept model
mean((mean(y[train])- y.test)^2)
```

```
## [1] 224669.9
```

```r
# Predictions for large lambda val
ridge.pred <-predict(ridge.mod, s = 1e10, newx = x[test, ])
mean((ridge.pred- y.test)^2) # Much higher MSE than lambda=4
```

```
## [1] 224669.8
```

```r
# Comparing with OLS model
ridge.pred <-predict(ridge.mod, s = 0, newx = x[test, ],
 exact = T, x = x[train, ], y = y[train]) # LS estimate
mean((ridge.pred- y.test)^2) # LS MSE
```

```
## [1] 168588.6
```

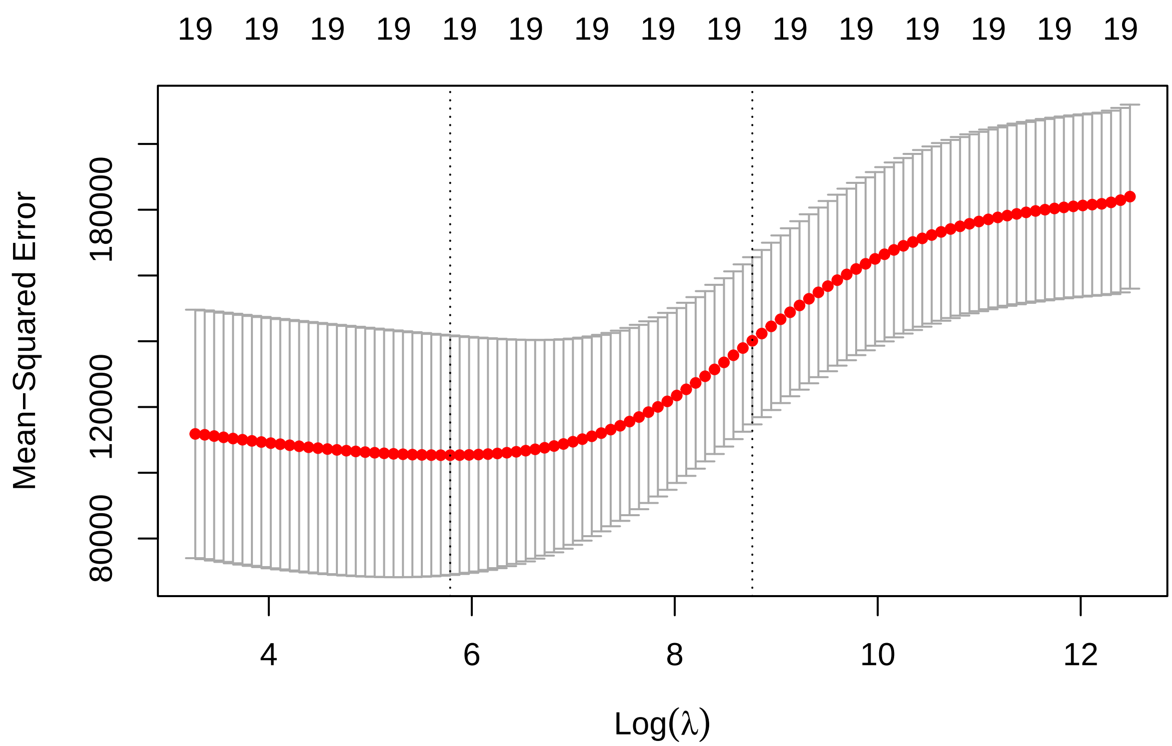
```r
lm(y ~ x, subset = train)
```

```
##
## Call:
## lm(formula = y ~ x, subset = train)
##
## Coefficients:
## (Intercept)       xAtBat        xHits       xHmRun        xRuns         xRBI
##    274.0145      -0.3521      -1.6377       5.8145       1.5424       1.1243
##      xWalks       xYears       xCAtBat       xCHits      xCHmRun       xCRuns
##      3.7287     -16.3773      -0.6412       3.1632       3.4008      -0.9739
##       xCRBI      xCWalks     xLeagueN    xDivisionW     xPutOuts     xAssists
##     -0.6005       0.3379     119.1486    -144.0831       0.1976       0.6804
##     xErrors  xNewLeagueN
##     -4.7128     -71.0951
```

```r
predict(ridge.mod, s = 0, exact = T, type = "coefficients",
x = x[train, ], y = y[train])[1:20, ] # This estimates the same as the lm() function
```

```
##  (Intercept)        AtBat         Hits        HmRun         Runs          RBI
##  274.0200994   -0.3521900   -1.6371383    5.8146692    1.5423361    1.1241837
##        Walks        Years       CAtBat        CHits       CHmRun        CRuns
##    3.7288406  -16.3795195   -0.6411235    3.1629444    3.4005281   -0.9739405
##         CRBI       CWalks      LeagueN    DivisionW      PutOuts      Assists
##   -0.6003976    0.3378422  119.1434637 -144.0853061    0.1976300    0.6804200
##       Errors   NewLeagueN
##   -4.7127879  -71.0898914
```

```r
### CROSS-VALIDATION ###
# We can use the built in cv.glmnet() to perform cv to choose optimal lambda
set.seed(1)
cv.out <-cv.glmnet(x[train, ], y[train], alpha = 0)
plot(cv.out)
```




```r
bestlam <- cv.out$lambda.min # Lambda val that minimizes cv error
bestlam
```

```
## [1] 326.0828
```

```r
# Redoing ridge regression with best lambda val
ridge.pred <-predict(ridge.mod, s = bestlam,
 newx = x[test, ])
mean((ridge.pred- y.test)^2) # Best MSE
```

```
## [1] 139856.6
```

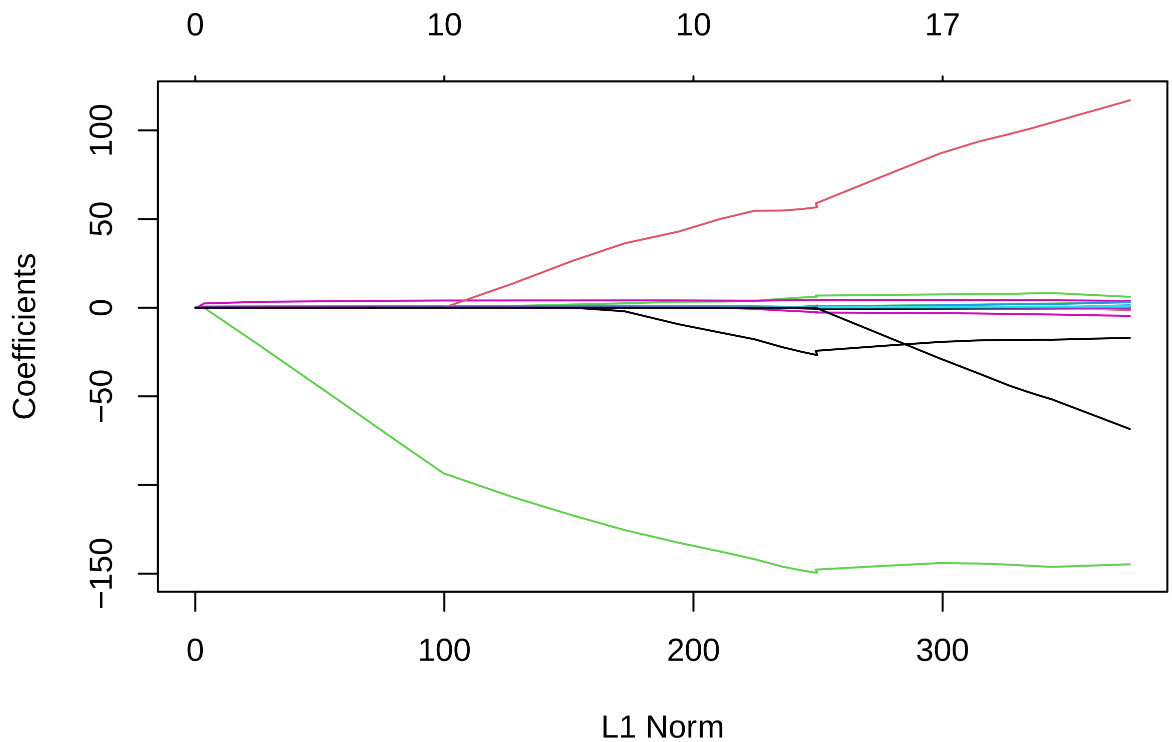
```r
# Optimal ridge model
out <-glmnet(x, y, alpha = 0)
predict(out, type = "coefficients", s = bestlam)[1:20, ]
```

```
##  (Intercept)        AtBat         Hits        HmRun         Runs          RBI
##  15.44383120   0.07715547   0.85911582   0.60103106   1.06369007   0.87936105
##        Walks        Years       CAtBat        CHits       CHmRun        CRuns
##   1.62444617   1.35254778   0.01134999   0.05746654   0.40680157   0.11456224
##         CRBI       CWalks      LeagueN    DivisionW      PutOuts      Assists
##   0.12116504   0.05299202  22.09143197 -79.04032656   0.16619903   0.02941950
##       Errors   NewLeagueN
##  -1.36092945   9.12487765
```

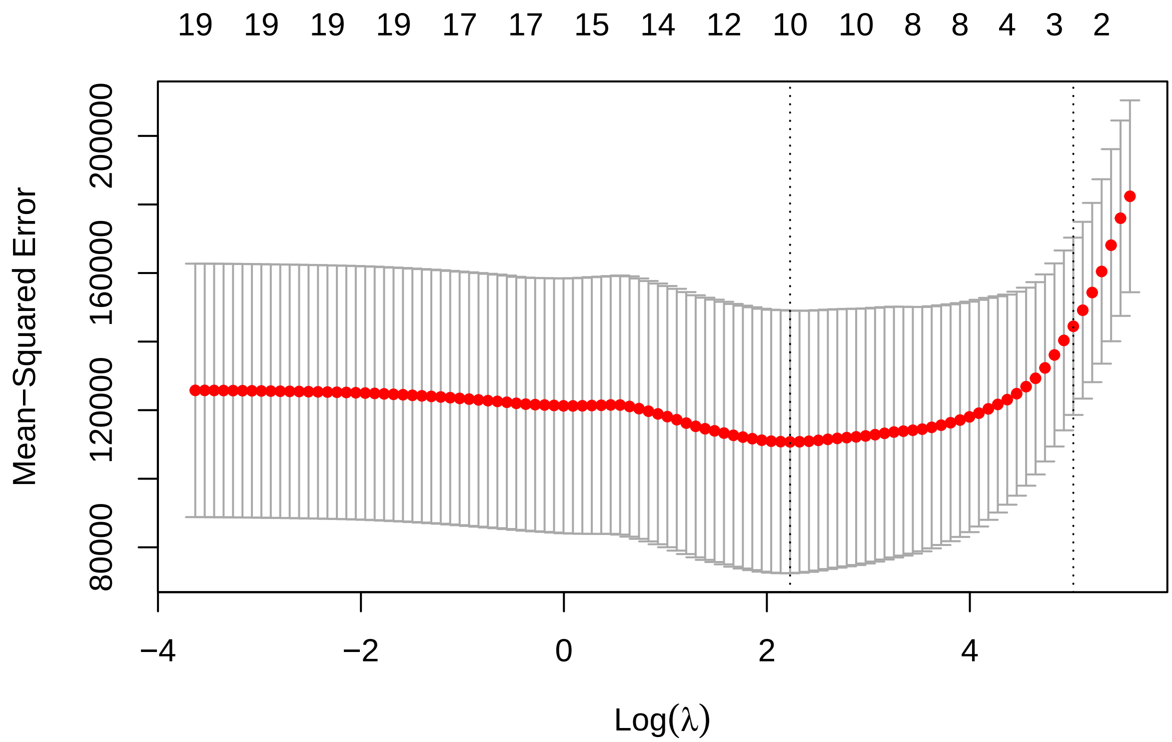
Section 6.5.2 (LASSO)

```r
# Lasso model with alpha=1
lasso.mod <-glmnet(x[train, ], y[train], alpha = 1,
 lambda = grid)
plot(lasso.mod)
```

```
## Warning in regularize.values(x, y, ties, missing(ties), na.rm = na.rm):
## collapsing to unique 'x' values
```




```
# We use CV again to determine optimal lambda
set.seed(1)
cv.out <-cv.glmnet(x[train, ], y[train], alpha = 1)
plot(cv.out)
```




```r
bestlam <- cv.out$lambda.min
lasso.pred <-predict(lasso.mod, s = bestlam,
 newx = x[test, ])
mean((lasso.pred- y.test)^2) # Lower than MSE for null and LS models
```

```
## [1] 143673.6
```

```r
# Predictions with best lambda
bestlam
```

```
## [1] 9.286955
```

```r
out <-glmnet(x, y, alpha = 1, lambda = grid)
lasso.coef <-predict(out, type = "coefficients",
 s = bestlam)[1:20, ]
lasso.coef # LASSO model with best lambda omly chooses 11 variables
```

```
##   (Intercept)         AtBat          Hits         HmRun          Runs 
##    1.27479059   -0.05497143    2.18034583    0.00000000    0.00000000 
##           RBI         Walks         Years        CAtBat         CHits 
##    0.00000000    2.29192406   -0.33806109    0.00000000    0.00000000 
##        CHmRun         CRuns          CRBI        CWalks       LeagueN 
##    0.02825013    0.21628385    0.41712537    0.00000000   20.28615023 
##     DivisionW       PutOuts       Assists        Errors    NewLeagueN 
## -116.16755870    0.23752385    0.00000000   -0.85629148    0.00000000
```

Section 6.5.3 (Principal Component Regression)

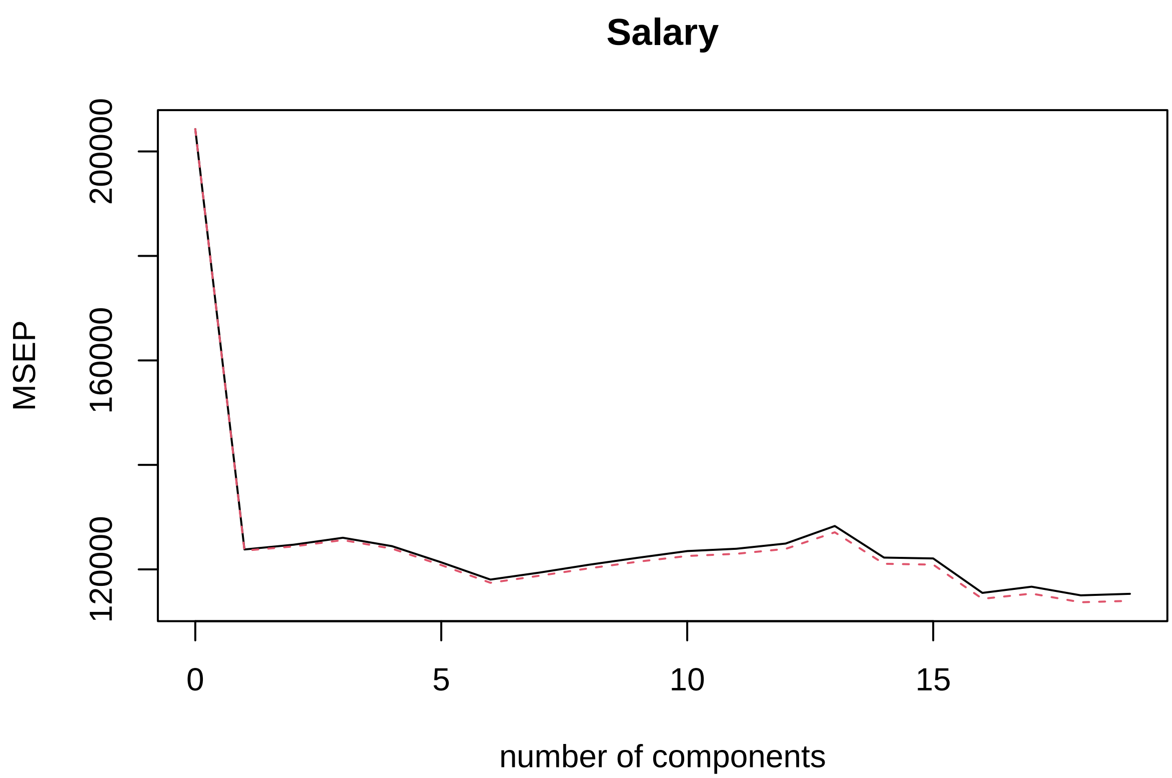
```r
# pls library contains pcr regression package
library(pls)
```

```
## Warning: package 'pls' was built under R version 4.4.3

##
## Attaching package: 'pls'

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

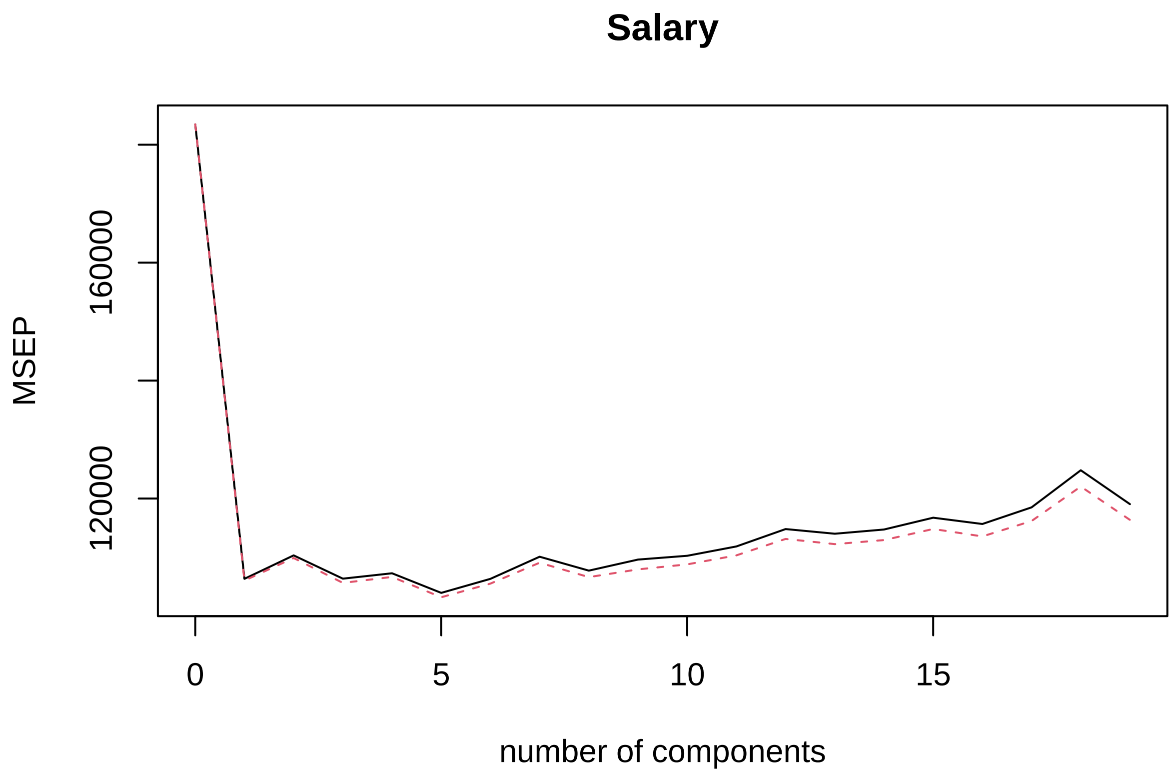
```r
set.seed(2)

# scale=TRUE standardizes predictors, validation="CV" uses CV for every possible
# value of M
pcr.fit <-pcr(Salary ~ ., data = Hitters, scale = TRUE,
 validation = "CV")
# Note that summary returns RMSE, so we must square to get MSE
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
```

```r
# val.type="MSEP" plots CV MSE to be plotted
validationplot(pcr.fit, val.type="MSEP")
```




```r
# Run PCR on training data and validate on test set
# Train
set.seed(1)
pcr.fit <-pcr(Salary ~ ., data = Hitters, subset = train,
 scale = TRUE, validation = "CV")
validationplot(pcr.fit, val.type = "MSEP") # Lowest CV error is at M=5
```




```r
# Test
pcr.pred <-predict(pcr.fit, x[test, ], ncomp = 5) # Predicting on test set
mean((pcr.pred- y.test)^2)
```

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

```r
pcr.fit <-pcr(y ~ x, scale = TRUE, ncomp = 5)
summary(pcr.fit)
```

```
## 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
## y    40.63    41.58    42.17    43.22    44.90
```

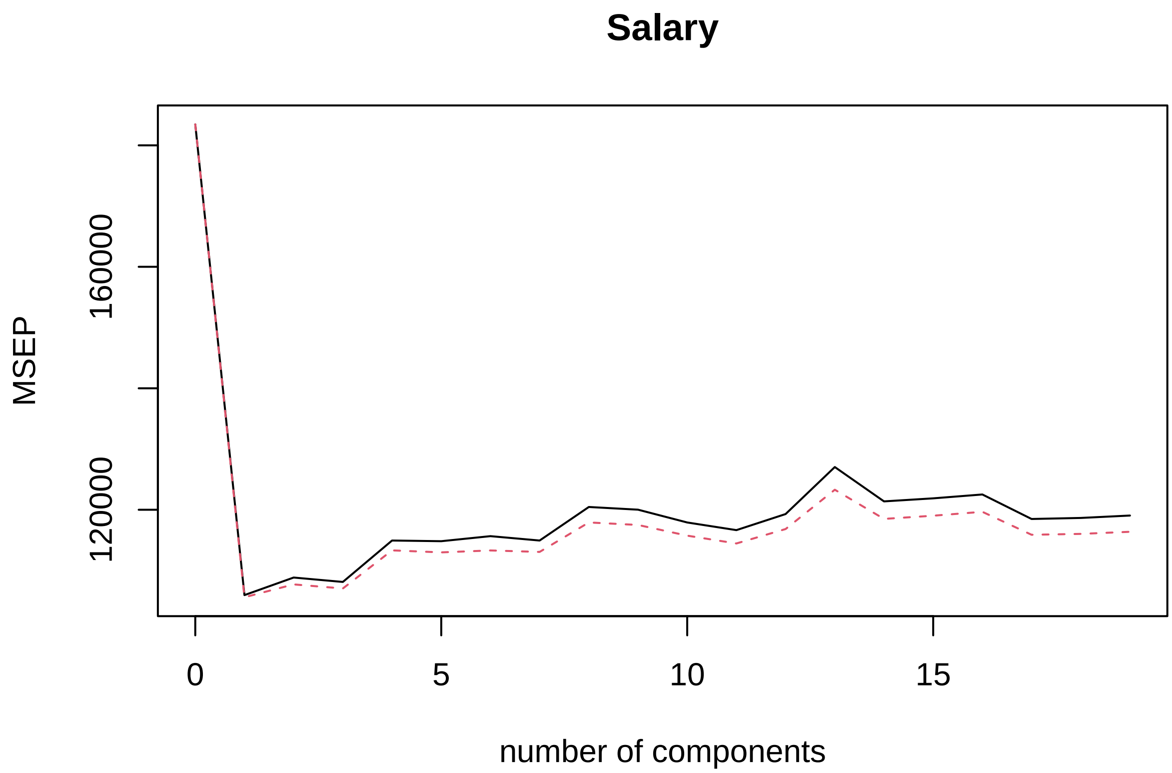
Section 6.5.3 (Partial Least Squares)

```r
set.seed(1)
# Fitting PLS model
```

```r
pls.fit <-plsr(Salary ~ ., data = Hitters, subset = train, scale= TRUE,
               validation = "CV")
summary(pls.fit)
```

```
## Data:    X dimension: 131 19
##  Y dimension: 131 1
## Fit method: kernelpls
## 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
```

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




```r
# CV error minimized when M=1. Now predict on test set
pls.pred <-predict(pls.fit, x[test, ], ncomp = 1)
mean((pls.pred- y.test)^2)
```

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

```r
# Now fit on whole dataset
pls.fit <-plsr(Salary ~ ., data = Hitters, scale = TRUE,
 ncomp = 1)
summary(pls.fit)
```

```
## 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
```