Week 4 Assignment: Yvonne Martinez

Business Problem

You work for a consulting company to understand the factors on which professional Baseball players' salaries depend.

You are given individual data for professional players in the Major League along with their 1986 performance measures and 1987 salary.

The business goal of the consulting firm is to model the logged salary of professional Baseball players with the available independent variables. Your findings will be used by the company clients to understand how exactly the logged salaries vary with the independent variables.

The data consists of 263 observations of 16 attributes. Below is a brief description of the variables in the data:

Attributes:

- **CrAtBat** Career Times at Bat
- **CrBB** Career Walks
- **CrHits** Career Hits
- **CrHome** Career Home Runs
- **CrRbi** Career RBIs
- **CrRuns** Career Runs
- **YrMajor** Years in the Major Leagues
- **nAssts** Assists in 1986
- **nAtBat** Times at Bat in 1986
- **nBB** Walks in 1986
- **nError** Errors in 1986
- **nHits** Hits in 1986
- **nHome** Home Runs in 1986
- **nOuts** Put Outs in 1986
- **nRBI** RBIs in 1986

- **nRuns** Runs in 1986

Outcome:

LogSalary: Log of 1987 Salary in $ Thousands

Below, the dataset is loaded and then split into a train and test sets in a 80:20 ratio. Your job is to use the training set to build the models in Parts 1-3. In Part 4, you will use the test set to check the model performance.

Do not change anything in this r chunk. Just run the code chunk and move to the next one

```
Loading required package: Matrix

Loaded glmnet 4.1-7
```

Part 1: Full Model on All Regressors

You will only use **trainData** in **Part 1.**

By using the **trainData**, fit a standard linear regression with the variable **logSalary** as the response and all other attributes as predictors. Name it as **model_full**.

Question #1

According to the **model_full** results, which regression coefficients are statistically significant at the 99% confidence level? Select all that apply.

```
#fit a standard linear regression with the variable logSalary as the response and all other attri
model_full <- lm(logSalary ~ ., data = trainData)
summary(model_full)
```

```
Call:
lm(formula = logSalary ~ ., data = trainData)

Residuals:
     Min       1Q   Median       3Q      Max 
-2.23518 -0.38604  0.05403  0.41878  1.26539 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  4.2375266  0.1761098  24.062  < 2e-16 ***
nAtBat      -0.0020377  0.0012827  -1.589 0.113778    
nHits        0.0123668  0.0047572   2.600 0.010051 *  
nHome        0.0075024  0.0117295   0.640 0.523177    
nRuns       -0.0037564  0.0059536  -0.631 0.528818    
```

```
nRBI        -0.0006802  0.0050769  -0.134 0.893558    
nBB          0.0123192  0.0035077   3.512 0.000553 ***
YrMajor      0.0808472  0.0235407   3.434 0.000726 ***
CrAtBat      0.0001220  0.0002560   0.477 0.634204    
CrHits      -0.0006232  0.0013110  -0.475 0.635080    
CrHome      -0.0005427  0.0030564  -0.178 0.859254    
CrRuns       0.0014737  0.0014468   1.019 0.309637    
CrRbi        0.0003649  0.0013122   0.278 0.781236    
CrBB        -0.0015703  0.0006199  -2.533 0.012100 *  
nOuts        0.0004799  0.0001641   2.924 0.003863 ** 
nAssts       0.0001767  0.0004413   0.400 0.689301    
nError      -0.0020375  0.0091949  -0.222 0.824867    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5602 on 194 degrees of freedom
Multiple R-squared:  0.6193,	Adjusted R-squared:  0.5879 
F-statistic: 19.72 on 16 and 194 DF,  p-value: < 2.2e-16
```

```r
# Get the regression results
summary(model_full)$coefficients
```

```
                 Estimate   Std. Error    t value     Pr(>|t|)
(Intercept)  4.2375266336 0.1761098353 24.0618397 3.840334e-60
nAtBat      -0.0020376716 0.0012826800 -1.5886048 1.137780e-01
nHits        0.0123668353 0.0047572285  2.5995882 1.005137e-02
nHome        0.0075023660 0.0117294886  0.6396158 5.231770e-01
nRuns       -0.0037564081 0.0059536028 -0.6309471 5.288178e-01
nRBI        -0.0006802062 0.0050769358 -0.1339797 8.935575e-01
nBB          0.0123192076 0.0035076666  3.5120806 5.530162e-04
YrMajor      0.0808472281 0.0235407122  3.4343578 7.262501e-04
CrAtBat      0.0001219822 0.0002559580  0.4765714 6.342037e-01
CrHits      -0.0006231532 0.0013109652 -0.4753392 6.350800e-01
CrHome      -0.0005426989 0.0030564221 -0.1775602 8.592537e-01
CrRuns       0.0014737384 0.0014467526  1.0186527 3.096365e-01
CrRbi        0.0003649257 0.0013122380  0.2780942 7.812362e-01
CrBB        -0.0015703150 0.0006199406 -2.5330089 1.210030e-02
nOuts        0.0004799025 0.0001641079  2.9243105 3.863220e-03
nAssts       0.0001766795 0.0004412550  0.4004023 6.893008e-01
nError      -0.0020374804 0.0091948797 -0.2215886 8.248672e-01
```

```r
#Get the  p values
summary(model_full)$coefficients[,4]
```

```
 (Intercept)       nAtBat        nHits        nHome        nRuns         nRBI 
3.840334e-60 1.137780e-01 1.005137e-02 5.231770e-01 5.288178e-01 8.935575e-01 
         nBB      YrMajor      CrAtBat       CrHits       CrHome       CrRuns 
5.530162e-04 7.262501e-04 6.342037e-01 6.350800e-01 8.592537e-01 3.096365e-01 
```

```
       CrRbi         CrBB        nOuts       nAssts       nError
7.812362e-01 1.210030e-02 3.863220e-03 6.893008e-01 8.248672e-01
```

```
# Get the coefficients with p values less than 0.01

names(which(summary(model_full)$coefficients[,4]<.01))
```

```
[1] "(Intercept)" "nBB"         "YrMajor"     "nOuts"
```

```
data.frame(coef=names(which(summary(model_full)$coefficients[,4]<.01)))
```

```
         coef
1 (Intercept)
2         nBB
3     YrMajor
4       nOuts
```

Question 2

Calculate the mean-squared prediction error (MSPE), the adjusted R^2 , AIC, and BIC criterion values for **model_full.** Enter your selection in Canvas by selecting the closest answer choice from the list.

```
# Insert your R code for Question 2 in here
# HINTS:
# You can whether manually calculate or use a package to calculate MSPE
# Adjusted R Square is stored under model_full R object
# You can consider using AIC() function in stats package to calculate the AIC value
# You can consider using BIC() function in stats package to calculate the BIC value
# If you want to print all your answers in one dataframe you can just put it in a dataframe with

# mean-squared prediction error (MSPE)
MSPE_fullmodel=mean(model_full$residuals^2)
MSPE_fullmodel
```

```
[1] 0.2885564
```

```
# Adjusted R-squared
RSquared_Adj_fullmodel<-summary(model_full)$adj.r.squared
RSquared_Adj_fullmodel
```

```
[1] 0.5878716
```

```
# AIC
AIC<-AIC(model_full)
AIC
```

```
[1] 372.5476
```

```
# BIC
BIC<-BIC(model_full)
BIC
```

```
[1] 432.8811
```

Question 3

So far, we did not do any feature selection. Instead, we have calculated the Adjusted R-squared, AIC, and BIC criterion values for the full model with all features are included as predictor in our largest model. In the following parts, we will choose the best sub-model based on one of these criterion values.

Now, your task is to predict **logSalary** with all the predictors in **trainData,** then calculate the mean squared prediction errors (MSPE) in the **trainData** based on 5-fold, 10-fold and leave one out cross-validation approaches?

Use **cv.glm** function in R to calculate the cross validated estimates. Use **set.seed(5410)** when you calculate the cross-validated estimates

Note: Is there an increase or decrease in MSPE with cross validation? You should be able to tell why MSPE is going up with cross-validation method.Since we assume you all know why, you are not required to enter your response in Canvas.

```
# Insert your R code for Question 3 in here
# HINTS:

# You can first create a linear model with glm() function modglm=glm(logSalary ~ ., data = trainD
# cv.glm(, K=5) gives  you the 5 fold-cross validation results
# cv.glm(, K=10) gives  you the 10 fold-cross validation results
# cv.glm(, K=n) gives  you the LOOCV results when n is the number of rows in trainData

# cv.glm() R object stores two information under delta (cv.glm()$delta). The first information gi

#set the seed
set.seed(5410)

#creating linear model using glm and using training data
modglm=glm(logSalary ~ ., data = trainData)

#calculate the mean squared prediction errors (MSPE) in the trainData based on 5-fold

cv5fold <- cv.glm(trainData, modglm, K = 5)
mspe_5fold <- cv5fold$delta[1]
print(mspe_5fold)
```

```
[1] 0.3603185
```

```
#calculate the mean squared prediction errors (MSPE) in the trainData based on 10-fold

cv10fold <- cv.glm(trainData, modglm, K = 10)
mspe_10fold <- cv10fold$delta[1]
print(mspe_10fold)
```

```
[1] 0.3544171
```

```
#calculate the mean squared prediction errors (MSPE) in the trainData based on leave one out cros

cvl <- cv.glm(trainData, modglm, K = nrow(trainData))
mspe_l <- cvl$delta[1]
print(mspe_l)
```

```
[1] 0.3530806
```

```
data.frame(CV5fold=mspe_5fold,  CV10fold=mspe_10fold, LeaveOO=mspe_l)
```

```
    CV5fold  CV10fold   LeaveOO
1 0.3603185 0.3544171 0.3530806
```

Part 2: Best Subset Model Search

You will only use **trainData** in Part 2.

Question 4

What is the total number of different models that can be built from all possible combinations of the predictors with p=16?

No coding is needed for Question 4. Just answer it in Canvas.

Question 5

Warning: This question can be challenging.

In this part, we will use **leaps** function in the **leaps** library in R to compare all possible models and decide on the best model by using Adjusted R-squared criteria on **trainData**.

Which set of predictors will give you the highest Adjusted R-squared value when we use the ***trainData*** to train all possible subset models. Use **leaps** function in the **leaps** library in R to compare all possible models and decide on the best model. You can use leaps package and set the **nbest** parameter to **1** to get the desired table.

The leaps function in R can help you to construct a table indicating the variables included in the best model of each size (p=1,p=2,..., p=16) and the corresponding Adjusted R-squared value. Hint: The table must include 16 rows, the best subset for each k. Check the lab help recordings for the details. You can use leaps package and set the nbest parameter to 1 to get the desired table. Alternatively, you can use `regsubsets` function in leaps package to get the same results.

```
# Insert your R code for Question 5 in here
# HINTS:
# You can store the predictor names with  col_names = names(trainData)[-17] and insert it into le
# nbest=1 will give   you the highest performing model for each set (models with  only 1 predicto

# After creating the leaps object, you can first fet the index of best model with which () functi
# In the leaps () output, the coefficient 1 in front a coefficient indicates it has been selected

# use all 16 subsets using regsubsets
leaps_md <- regsubsets(logSalary ~ ., data = trainData, nvmax = 16, nbest=1)

# Get the best subset model with the highest adjusted R-squared
best_subset <- summary(leaps_md)$which[which.max(summary(leaps_md)$adjr2),]
print(best_subset)
```

```
(Intercept)      nAtBat       nHits       nHome       nRuns        nRBI
       TRUE        TRUE        TRUE       FALSE       FALSE       FALSE
        nBB     YrMajor     CrAtBat      CrHits      CrHome      CrRuns
       TRUE        TRUE       FALSE       FALSE       FALSE        TRUE
      CrRbi        CrBB       nOuts      nAssts      nError
      FALSE        TRUE        TRUE       FALSE       FALSE
```

```
# Get the names of the predictors in the best subset model
predictor_names <-names(trainData)[-1]
best_predictors <- predictor_names[best_subset[-1]]

print(best_predictors)
```

```
[1] "nHits"   "nHome"   "YrMajor" "CrAtBat" "CrRbi"   "nOuts"   "nAssts"
```

```
data.frame(prednames=best_predictors)
```

```
  prednames
1     nHits
2     nHome
3   YrMajor
4   CrAtBat
5     CrRbi
```

```
6     nOuts
7    nAssts
```

Part 3: Regularized Regression

You will only use **trainData** in Part 3.

Question 6

Now, we will use the **trainData** and perform RIDGE regression on the full model (**model_full**). Before performing Ridge regression, we need to standardize the predictors but there are some packages that standardize variables for you. In that case, there is no need to standardize predictors twice. For this RLab assignment, please use **glmnet** package so that you do not have to worry about standardizing your features.

Your task is to write an R code to apply Ridge regression on **trainData** set with **10-fold cross validation**. Print the optimized lambda value and the minimum mean cross-validated Error. Keep the default loss function (t**ype.measure="mse"**).

```
# Insert your R code for Question 6 in here
# HINTS:
# in cv.glmnet() function choose  family='gaussian', type.measure="mse", alpha=0, nfolds=10 for t
# optimized lamba is stored under the cv.glmnet() R object
# Minimum Mean CV Error is stored under cv.glmnet() R object

# Optimize lambda using 10-fold cross validation
set.seed(5410)

#make into a matrix

y <- trainData$logSalary
x <- as.matrix(trainData[,-17])

#RIDGE regression using glmnet package
ridge <- cv.glmnet(x, y, family = 'gaussian', type.measure = "mse", alpha = 0, nfolds = 10)

#Print the optimized lambda value
optlambda <- ridge$lambda.min
print(optlambda)
```

```
[1] 0.08008381
```

```
#Print minimum mean cross-validated Error
```

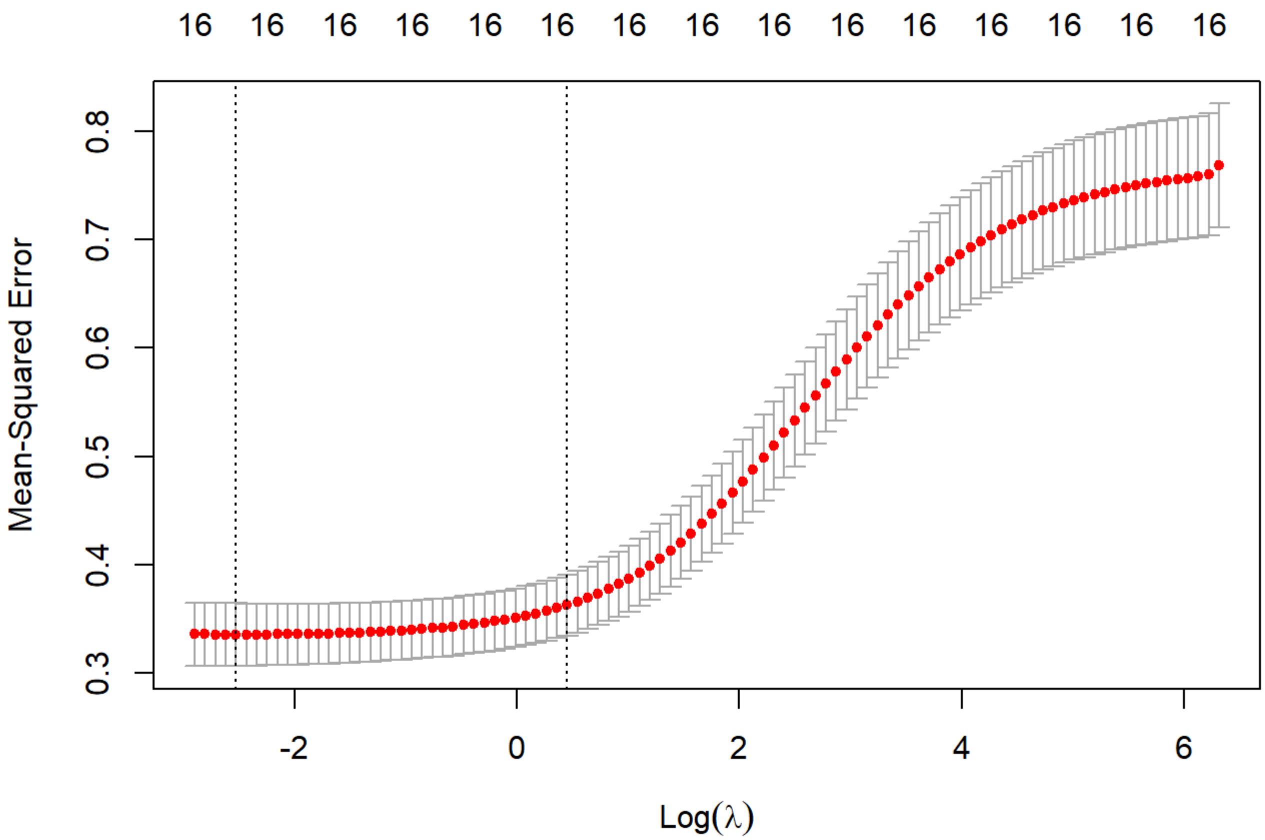
```
minmse <- ridge$cvm[which.min(ridge$cvm)]
print(minmse)
```

```
[1] 0.3358273
```

```
data.frame(optimized_lv=optlambda, min_mcv_Error=minmse)
```

```
  optimized_lv min_mcv_Error
1   0.08008381     0.3358273
```

```
################practice 4 code from professor#########################

## Find the optimal lambda using 10-fold CV
# set alpha=0  for RIDGE
# set alpha=1  for LASSO
# set alpha=0.5  for ELASTIC NET
# predictors and the target variable


y.train = trainData$logSalary
predictors.train = trainData[,-17]

y.test = testData$logSalary
predictors.test = testData[,-17
                           ]




set.seed(5410)
# Optimize lambda using 10-fold cross validation, keep the default lambda selection

RidgeCV = cv.glmnet(as.matrix(predictors.train), y.train,
                    family='gaussian', type.measure="mse", alpha=0, nfolds=10)




# plot
plot(RidgeCV)
```




```
# check the values of lambda used in the fits

RidgeCV$lambda
```

```
  [1] 551.98664459 502.94967242 458.26900971 417.55765393 380.46298279
  [6] 346.66370000 315.86705234 287.80629397 262.23837604 238.94184148
 [11] 217.71490683 198.37371456 180.75074050 164.69334288 150.06244021
 [16] 136.73130661 124.58447418 113.51673286 103.43221918  94.24358590
 [21]  85.87124548  78.24268070  71.29181659  64.95844809  59.18771860
 [26]  53.92964481  49.13868380  44.77333856  40.79579856  37.17161226
 [31]  33.86938867  30.86052553  28.11896150  25.62095046  23.34485583
 [36]  21.27096318  19.38130944  17.65952733  16.09070359  14.66124983
 [41]  13.35878480  12.17202718  11.09069783  10.10543080   9.20769218
 [46]   8.38970619   7.64438781   6.96528147   6.34650506   5.78269904
 [51]   5.26898000   4.80089834   4.37439976   3.98579014   3.63170353
 [56]   3.30907300   3.01510407   2.74725054   2.50319237   2.28081566
 [61]   2.07819428   1.89357323   1.72535340   1.57207776   1.43241871
 [66]   1.30516658   1.18921918   1.08357222   0.98731065   0.89960069
 [71]   0.81968265   0.74686430   0.68051493   0.62005986   0.56497545
 [76]   0.51478459   0.46905255   0.42738321   0.38941567   0.35482105
 [81]   0.32329973   0.29457867   0.26840911   0.24456439   0.22283796
 [86]   0.20304165   0.18500399   0.16856875   0.15359356   0.13994873
```

```
[91]  0.12751607  0.11618790  0.10586608  0.09646123  0.08789188
[96]  0.08008381  0.07296939  0.06648699  0.06058047  0.05519866
```

```
# check the mean cross-validated error for each lambda used

RidgeCV$cvm
```

```
 [1] 0.7679549 0.7598305 0.7576884 0.7566163 0.7554446 0.7541646 0.7527668
 [8] 0.7512412 0.7495769 0.7477623 0.7457852 0.7436324 0.7412901 0.7387436
[15] 0.7359777 0.7329757 0.7297220 0.7261991 0.7223895 0.7182752 0.7138386
[22] 0.7090620 0.7039282 0.6984208 0.6925244 0.6862254 0.6795120 0.6723749
[29] 0.6648079 0.6568083 0.6483776 0.6395218 0.6302523 0.6205860 0.6105456
[36] 0.6001602 0.5894658 0.5785037 0.5673201 0.5559687 0.5445072 0.5329969
[43] 0.5215019 0.5100876 0.4988194 0.4877613 0.4769743 0.4665151 0.4564347
[50] 0.4467777 0.4375807 0.4288709 0.4206707 0.4129924 0.4058403 0.3992113
[57] 0.3930958 0.3874785 0.3823388 0.3776527 0.3733932 0.3695313 0.3660374
[64] 0.3628815 0.3600345 0.3574683 0.3551552 0.3530691 0.3511931 0.3495030
[71] 0.3479827 0.3466148 0.3453825 0.3442671 0.3432613 0.3423601 0.3415460
[78] 0.3408089 0.3401454 0.3395523 0.3390156 0.3385331 0.3381031 0.3377217
[85] 0.3373805 0.3370776 0.3368124 0.3365861 0.3363904 0.3362294 0.3360910
[92] 0.3359878 0.3359071 0.3358496 0.3358275 0.3358273 0.3358534 0.3358974
[99] 0.3359693 0.3360225
```

```
# get the minimum mean cross-validated error

min(RidgeCV$cvm)
```

```
[1] 0.3358273
```

```
# # number of non-zero coefficients at each lambda. For Ridge, it is all same and equal to number
# RidgeCV$nzero

# get the value of lambda which gives you the minimum cross-validated error

RidgeCV$lambda.min
```

```
[1] 0.08008381
```

```
# Use the best lambda and predict the target variable in the test set, calculate MSPE

RidgePredictTest<-predict(RidgeCV,s=RidgeCV$lambda.min,newx=as.matrix(predictors.test))


# Calculate the MSPE in the test set

MSPE_Ridge_test<-mean((RidgePredictTest-y.test)^2)
```

```
data.frame(optimized_lv=RidgeCV$lambda.min, min_mcv_Error=min(RidgeCV$cvm) )
```

```
  optimized_lv min_mcv_Error
1   0.08008381     0.3358273
```

Question 7

Now, we will use the **trainData** and perform **LASSO** regression on the full model (**model_full**). Please use **glmnet** package so that you do not have to worry about standardizing your features.

Your task is to write an R code to apply **LASSO** regression on **trainData** set with **10-fold cross validation.** Print the optimized lambda value and the minimum mean cross-validated Error. Keep the default loss function (type.measure="mse").

```
# Insert your R code for Question 7 in here
# HINTS:
# in cv.glmnet() function choose  family='gaussian', type.measure="mse", alpha=0, nfolds=10 for t
# optimized lamba is stored under the cv.glmnet() R object
# Minimum Mean CV Error is stored under cv.glmnet() R object
# set alpha=0  for RIDGE
# set alpha=1  for LASSO

set.seed(5410)

# Convert trainData to matrix format
X <- as.matrix(trainData[, -17])
y <- trainData$logSalary

# Perform LASSO regression with 10-fold cross validation
lasso_fit <- cv.glmnet(X, y, family = "gaussian", type.measure = "mse", alpha = 1, nfolds = 10)

# Print the optimized lambda value and the minimum mean cross-validated error
cat("Optimal lambda value:", lasso_fit$lambda.min, "\n")
```

```
Optimal lambda value: 0.02811896
```

```
cat("Minimum mean cross-validated error:", lasso_fit$cvm[lasso_fit$lambda == lasso_fit$lambda.min
```

```
Minimum mean cross-validated error: 0.3273982
```

```
################practice 4 code from professor########################

## Find the optimal lambda using 10-fold CV
# set alpha=0  for RIDGE
# set alpha=1  for LASSO
```

```
# set alpha=0.5  for ELASTIC NET
# predictors and the target variable


y.train = trainData$logSalary
predictors.train = trainData[,-17]

y.test = testData$logSalary
predictors.test = testData[,-17]




set.seed(5410)
# Optimize lambda using 10-fold cross validation, keep the default lambda selection


LassoCV = cv.glmnet(as.matrix(predictors.train), y.train,
                    family='gaussian', type.measure="mse", alpha=1, nfolds=10)




# check the values of lambda used in the fits

LassoCV$lambda
```

```
 [1] 5.519866e-01 5.029497e-01 4.582690e-01 4.175577e-01 3.804630e-01
 [6] 3.466637e-01 3.158671e-01 2.878063e-01 2.622384e-01 2.389418e-01
[11] 2.177149e-01 1.983737e-01 1.807507e-01 1.646933e-01 1.500624e-01
[16] 1.367313e-01 1.245845e-01 1.135167e-01 1.034322e-01 9.424359e-02
[21] 8.587125e-02 7.824268e-02 7.129182e-02 6.495845e-02 5.918772e-02
[26] 5.392964e-02 4.913868e-02 4.477334e-02 4.079580e-02 3.717161e-02
[31] 3.386939e-02 3.086053e-02 2.811896e-02 2.562095e-02 2.334486e-02
[36] 2.127096e-02 1.938131e-02 1.765953e-02 1.609070e-02 1.466125e-02
[41] 1.335878e-02 1.217203e-02 1.109070e-02 1.010543e-02 9.207692e-03
[46] 8.389706e-03 7.644388e-03 6.965281e-03 6.346505e-03 5.782699e-03
[51] 5.268980e-03 4.800898e-03 4.374400e-03 3.985790e-03 3.631704e-03
[56] 3.309073e-03 3.015104e-03 2.747251e-03 2.503192e-03 2.280816e-03
[61] 2.078194e-03 1.893573e-03 1.725353e-03 1.572078e-03 1.432419e-03
[66] 1.305167e-03 1.189219e-03 1.083572e-03 9.873107e-04 8.996007e-04
[71] 8.196826e-04 7.468643e-04 6.805149e-04 6.200599e-04 5.649755e-04
[76] 5.147846e-04 4.690525e-04 4.273832e-04 3.894157e-04 3.548211e-04
[81] 3.232997e-04 2.945787e-04 2.684091e-04 2.445644e-04 2.228380e-04
[86] 2.030417e-04 1.850040e-04 1.685687e-04 1.535936e-04 1.399487e-04
[91] 1.275161e-04 1.161879e-04 1.058661e-04 9.646123e-05 8.789188e-05
```

```
# check the mean cross-validated error for each lambda used

LassoCV$cvm
```

```
 [1] 0.7626211 0.7187932 0.6760854 0.6392750 0.5997779 0.5604548 0.5271149
 [8] 0.4992653 0.4757857 0.4561568 0.4394270 0.4245270 0.4101772 0.3974488
[15] 0.3863127 0.3761086 0.3671351 0.3597222 0.3535889 0.3485056 0.3442905
[22] 0.3407671 0.3378377 0.3354091 0.3333952 0.3317336 0.3304095 0.3293499
[29] 0.3285591 0.3279986 0.3276412 0.3274580 0.3273982 0.3274368 0.3274758
[36] 0.3275753 0.3276430 0.3277422 0.3279767 0.3284754 0.3291566 0.3297704
[43] 0.3303295 0.3304384 0.3308049 0.3314659 0.3323501 0.3332565 0.3341670
[50] 0.3350029 0.3358140 0.3363474 0.3368794 0.3374337 0.3378634 0.3382775
[57] 0.3386807 0.3389410 0.3392166 0.3395085 0.3398727 0.3402306 0.3405162
[64] 0.3407739 0.3410502 0.3412376 0.3415589 0.3418119 0.3421818 0.3426265
[71] 0.3431192 0.3436312 0.3441581 0.3446797 0.3452148 0.3456916 0.3460967
[78] 0.3464822 0.3467951 0.3470576 0.3473081 0.3476005 0.3478981 0.3481523
[85] 0.3483630 0.3485405 0.3487013 0.3488507 0.3489915 0.3491191 0.3492364
[92] 0.3493366 0.3494263 0.3495150 0.3495930
```

```r
# get the minimum mean cross-validated error

min(LassoCV$cvm)
```

```
[1] 0.3273982
```

```r
# optimal lambda

LassoCV$lambda.min
```

```
[1] 0.02811896
```

```r
# number of non-zero coefficients at each lambda.
LassoCV$nzero
```

```
 s0  s1  s2  s3  s4  s5  s6  s7  s8  s9 s10 s11 s12 s13 s14 s15 s16 s17 s18 s19
  0   1   2   2   3   3   3   4   4   4   4   5   5   5   6   7   7   7   7   7
s20 s21 s22 s23 s24 s25 s26 s27 s28 s29 s30 s31 s32 s33 s34 s35 s36 s37 s38 s39
  7   7   7   7   7   7   7   7   7   7   7   7   7   7   8   9   9   9   9   9
s40 s41 s42 s43 s44 s45 s46 s47 s48 s49 s50 s51 s52 s53 s54 s55 s56 s57 s58 s59
 10  10  10  10  10   9  10  11  11  12  12  12  12  13  13  13  13  13  13  13
s60 s61 s62 s63 s64 s65 s66 s67 s68 s69 s70 s71 s72 s73 s74 s75 s76 s77 s78 s79
 14  14  15  15  15  14  14  14  14  14  14  14  14  15  15  15  15  15  15  15
s80 s81 s82 s83 s84 s85 s86 s87 s88 s89 s90 s91 s92 s93 s94
 16  16  16  16  16  16  16  16  16  16  16  16  16  15  15
```

```r
# numnber of features at the optimal lambda
LassoCV$nzero[LassoCV$lambda == LassoCV$lambda.min]
```

```
s32
  7
```

```
# Use the best lambda and predict the target variable in the test set with Lasso and  calculate M

LassoPredictTest<-predict(LassoCV,s=LassoCV$lambda.min,newx=as.matrix(predictors.test))


MSPE_Lasso_test<-mean((LassoPredictTest-y.test)^2)



data.frame(optimized_lv=LassoCV$lambda.min, min_mcv_Error=min(LassoCV$cvm) )
```

```
  optimized_lv min_mcv_Error
1   0.02811896     0.3273982
```

Question 8

Which variables were selected based on LASSO?

```
# Insert your R code for Question 7 in here
# HINTS: use coef() to extract the coefficients. Any coefficient with 0 estimate is dropped from

lasso_coef <- coef(LassoCV, s = LassoCV$lambda.min)
selected_vars <- rownames(lasso_coef)[lasso_coef[,1] != 0]
print(selected_vars)
```

```
[1] "(Intercept)" "nHits"       "nRBI"        "nBB"         "YrMajor"
[6] "CrHits"      "CrRbi"       "nOuts"
```

```
# Insert your R code for Question 7 in here
# HINTS: use coef() to extract the coefficients. Any coefficient with 0 estimate is dropped from
# Fit Lasso model
# Fit Lasso model
# Fit Lasso model
LassoCV = cv.glmnet(as.matrix(predictors.train), y.train,
                    family='gaussian', type.measure="mse", alpha=1, nfolds=10)


# Get coefficients for optimal lambda
opt_lambda = LassoCV$lambda.min
coef_LassoCV = coef(LassoCV, s=opt_lambda)

print(coef_LassoCV)
```

```
17 x 1 sparse Matrix of class "dgCMatrix"
                      s1
```

```
(Intercept)  4.226378e+00
nAtBat       .
nHits        6.229214e-03
nHome        3.335577e-04
nRuns        .
nRBI         9.501867e-04
nBB          5.541235e-03
YrMajor      6.741847e-02
CrAtBat      .
CrHits       1.685110e-04
CrHome       .
CrRuns       .
CrRbi        2.575131e-05
CrBB         .
nOuts        3.876770e-04
nAssts       .
nError      -1.743525e-04
```

PART 4

You will only use **testData** in Part 4.

Now, it is time to put all the fitted models a test. Predict **logSalary** for each of the rows in the test data, **testData**, using model_full in Part 1, best subset model in Part 2, and Ridge and Lasso Regression models in Part 3.

Calculate the MSPE on the test set for each model and insert your answer in Canvas.

```
#  Insert your R code for Question 7 in here

OLSmodel<-lm(logSalary~.,data=testData)
OLSPredictTest<-predict(OLSmodel,newx=as.matrix(predictors.test))
MSPE_OLS_test<-mean((OLSPredictTest-y.test)^2)



# performance comparison
# OLS
MSPE_OLS_test
```

```
[1] 0.2048143
```

```
# Ridge
MSPE_Ridge_test
```

```
[1] 0.4300489
```

```
#Lasso
MSPE_Lasso_test
```

```
[1] 0.4287379
```

```
data.frame(MSPE_OLS_test=MSPE_OLS_test, MSPE_Ridge_test=MSPE_Ridge_test,MSPE_Lasso_test=MSPE_Lass
```

```
  MSPE_OLS_test MSPE_Ridge_test MSPE_Lasso_test
1     0.2048143       0.4300489       0.4287379
```