Regularization and logistic regression

BitTiger DS501 Week 3 HW Meina Wang

Question 1

Suppose we fit “Lasso Regression” to a data set, which has 100 features (X1,X2…X100). Now, we rescale one of these feature by multiplying with 10 (say that feature is X1), and then refit Lasso regression with the same regularization parameter. Now, which of the following option will be correct?
A. It is more likely for X1 to be excluded from the model
B. It is more likely for X1 to be included in the model
C. Can’t say
D. None of these

Answer 1

B.

Multiplying the feature by 10 will lead to smaller coefficient assigned to this feature. Smaller coef will have less penalty by LASSO, thus would be more likely to be included in the model.

Question 2

Suppose you have fitted a multiple regression model on a dataset. Now, you are using Ridge regression with tuning parameter lambda to reduce its complexity. Choose the options below which describes relationship of bias and variance with lambda.
A. In case of very large lambda; bias is low, variance is low
B. In case of very large lambda; bias is low, variance is high
C. In case of very large lambda; bias is high, variance is low
D. In case of very large lambda; bias is high, variance is high

Answer 2

C.

Very large lambda would penaliza the parameters heavily, thus decreasing variance, but increasing bias (likely to underfit)

Question 3

Write a function to realize gradient descent in R. Understand how learning rate affects convergence.

Answer 3

From class slides, gradient descent steps:

- Step 0: find an initial $\beta_j^{(0)}$
- Step 1: $\beta_j^{(t+1)} := \beta_j^{(t)} - \eta \frac{\partial l(\beta)}{\partial \beta_j}$, where η is learning rate, and $\frac{\partial l(\beta)}{\partial \beta_j}$ is gradient.
- step 2: check if $\Delta_\beta l(\beta) \leq \epsilon$, where ϵ is the convergence threshold. If not, repeat step 1.

In [2]:

```
gradientDescent<-function(y, X, learning_rate, convergence_threshold, iters){

    X = as.matrix(data.frame(rep(1,length(y)),X))
    N = dim(X)[1]
    beta.init = as.matrix(rnorm(n=dim(X)[2], mean=0,sd = 1)) # initialize beta
    beta.init = t(beta.init)
    error = t(y) - beta.init%*%t(X)
    grad.init = -(2/N)%*%(error)%*%X # initialize gradient # %*% is operator for the
    beta = beta.init - learning_rate*(1/N)*grad.init
    convergence_threshold = 0.0001
    for(i in 1:iters){ # starts from 1
        error = t(y) - beta%*%t(X)
        grad = -(2/N)%*%error%*%X
        beta = tbeta - learning_rate*(2/N)*grad
        if(sqrt(sum(grad^2)) <= convergence_threshold){
            break
        }
    }
  print("Algorithm converged")
  print(paste("Final gradient norm is",sqrt(sum(grad^2))))
  values<-list("coef" = t(beta), "l2loss" = l2loss)
  return(values)
}
```

Learning rate determines how fast or slow each step takes towards the optimal weights (minimize cost function). If learning rate is very large we will skip the optimal solution (global minimum). If it is too small we might be trapped at local minimum, or will need too many iterations to converge to the best values.

Question 4

A five year follow-up study on 600 disease free subjects was carried out to assess the effect of whether having exposure E or not (of smoking for example) on the development (or not) of a certain disease. The variables AGE (continuous) and obesity status (boolean), which were determined at the start of the follow-up and were to be considered as control variables in analyzing the data.
(1) State the logit form of a logistic regression model that assesses the effect of the 0/1 exposure variable E controlling for the confounding effects of AGE and OBS and the interaction effects of AGE with E and OBS with E.
(2) Given above model you have, give a formula for the odds ratio for the exposure-disease relationship that controls for the confounding and interactive effects of AGE and OBS.
(3) Now use the formula from above to write an expression for the estimated odds ratio for the exposure-disease relationship when AGE=40 and OBS=1.

Answer 4

(1)
$logit(P) = \beta_0 + \beta_1 * E + \beta_2 * AGE + \beta_3 * OBS + \beta_4 * AGE * E + \beta_5 * OBS * E$
P is the probability of the development of a certain disease.
E is the exposure variable, and AGE and OBS are the control variables. β is the coefficient for each variable. The last two terms on the right hand side of the equation above are interaction effects of AGE with E and OBS with E.

(2)
Odds ratio for the exposure-disease relationship = $\frac{p}{1-p}$ = $\frac{probability\ of\ disease\ WITH\ exposure}{probability\ of\ disease\ WITHOUT\ exposure}$

$logit(P) = log(\frac{p}{1-p}) = log(odds)$
Taking e to the power to both sides of the above equation yields,
$e^{log(odds)} = odds = e^{log(\frac{p}{1-p})}$

Thus, the odds ratio for comparing WITH and WITHOUT exposure is
$\frac{odds_{WITH\ exposure}}{odds_{WITHOUT\ exposure}} = \frac{\frac{p_1}{1-p_1}}{\frac{p_2}{1-p_2}} = exp(logit(P_1))/exp(logit(P_2)) = exp(logit(P_1) - logit(P_2)) =$
$exp((\beta_0 + \beta_1 * 1 + \beta_2 * AGE_! + \beta_3 * OBS_1 + \beta_4 * AGE_1 * 1 + \beta_5 * OBS_1 * 1) - (\beta_0 + \beta_1 * 0 + \beta_2 * A$
$* OBS_2 * 0)) =$
$exp((\beta_0 + \beta_1 + \beta_2 * AGE_1 + \beta_3 * OBS_1 + \beta_4 * AGE_1 + \beta_5 * OBS_1) - (\beta_0 + \beta_2 * AGE_2 + \beta_3 * OBS_2))$
$exp(\beta_1 + \beta_2 * (AGE_1 - AGE_2) + \beta_3 * (OBS_1 - OBS_2) + \beta_4 * AGE + \beta_5 * OBS)$

Therefore, the odds ratio is
$exp(\beta_1 + \beta_2 * (AGE_1 - AGE_2) + \beta_3 * (OBS_1 - OBS_2) + \beta_4 * AGE + \beta_5 * OBS)$, where subscript 1 indicates the AGE and OBS values when E is WITH exposure, while subscript 2 indicates the values when E is WITHOUT exposure.

(3)
Plug in AGE = 40 and OBS = 1 into the equation from (2) yields,

$$exp(\beta_1 + \beta_2 * (40 - 40) + \beta_3 * (1 - 1) + \beta_4 * 40 + \beta_5 * 1) =$$
$$exp(\beta_1 + \beta_4 * 40 + \beta_5 * 1)$$

Question 5

Build the best logistic regression model to predict loan will be default (delay) or not. Add regularization to control for multicollinearity.

Answer 5

In [1]:

```
# load the data
loan <- read.csv("/users/meinawang/Documents/bittiger/DS501/lending-club-loan-data/
loanT <- loan
```

In [2]:

```
# select only features with no more than 20% missing data
loan$dti <- ifelse(!is.na(loan$dti_joint), loan$dti_joint, loan$dti)
loan$annual_inc <- ifelse(!is.na(loan$annual_inc_joint), loan$annual_inc_joint, loa
num.NA <- sort(sapply(loan, function(x) {sum(is.na(x))}), decreasing=TRUE)
remain.col <- names(num.NA)[which(num.NA <= 0.8 * dim(loan)[1])]
loan <- loan[, remain.col]
```

In [3]:

```
# based on last week's hw, log transform features so that they are close to normal d
loan$home_ownership <- ifelse(loan$home_ownership %in% c('ANY', 'NONE', 'OTHER'), 'O
                              loan$home_ownership)
int_state <- by(loan, loan$addr_state, function(x) {
  return(mean(x$int_rate))
})
loan$state_mean_int <-
  ifelse(loan$addr_state %in% names(int_state)[which(int_state <=
                                                      quantile(int_state, 0.25))],
         ifelse(loan$addr_state %in% names(int_state)[which(int_state <=
                                                             quantile(int_state, 0.
                ifelse(loan$addr_state %in% names(int_state)[which(int_state <= quan
                       'mediumhigh', 'high')))
loan$tot_cur_bal[which(is.na(loan$tot_cur_bal))] <- median(loan$tot_cur_bal, na.rm =
loan$total_acc[which(is.na(loan$total_acc))] <- median(loan$total_acc, na.rm = T)
loan$open_acc[which(is.na(loan$open_acc))] <- median(loan$open_acc, na.rm = T)
loan$annual_inc[which(is.na(loan$annual_inc))] <- median(loan$annual_inc, na.rm = T)
loan$tot_coll_amt[which(is.na(loan$tot_coll_amt))] <- median(loan$tot_coll_amt, na.r
loan$inq_last_6mths[which(is.na(loan$inq_last_6mths))] <- median(loan$inq_last_6mths
loan$log_annual_inc <- log(loan$annual_inc + 1)
loan$log_last_pymnt_amnt <- log(loan$last_pymnt_amnt + 1)
loan$log_tot_coll_amt <- log(loan$tot_coll_amt + 1)
loan$total_rev_hi_lim_log = log(loan$total_rev_hi_lim + 1)
loan$total_rec_int_log = log(loan$total_rec_int + 1)
```

In [4]:

```
# check the levels from feature loan_status
loan$loan_status <- gsub('Does not meet the credit policy. Status:', '', loan$loan_s
sort(table(loan$loan_status))

nums <- sapply(loan, is.numeric)
loan_nums <- loan[, nums]

categories <- sapply(loan, is.character)
loan_categories <- loan[, categories]
```

```
           Default  Late (16-30 days)     In Grace Period                  I
ssued
              1219               2357                6253
8460
Late (31-120 days)        Charged Off         Fully Paid                  Cu
rrent
             11591              46009             209711                   6
01779
```

In [6]:

```
# Convert the levels in loan_status into binary, 'Default', 'Charged Off', 'Late (1
#'Late (31-120 days)','Charged Off' are 1, the rest levels are 0.

loan$loan_status_binary <- with(loan, ifelse(loan_status  %in% c('Default', 'Charged
                                                                 'In Grace Period',
                                                                 'Charged Off'), 1,
table(loan$loan_status_binary)

loan$loan_status_binary = factor(loan$loan_status_binary)
levels(loan$loan_status_binary)
```

```
     0      1 
819950  67429 
```

'0' '1'

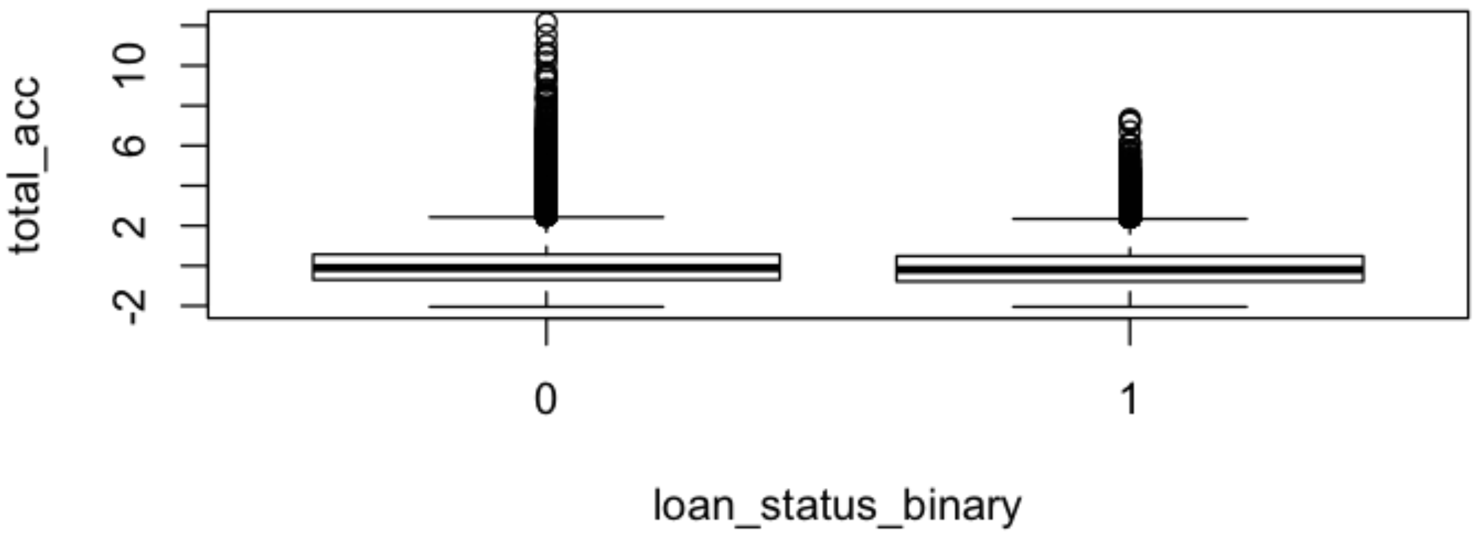
In [20]:

```
# check the pdf of features, and see if they are normal.
library(repr)

# Change plot size to 6 x 3
options(repr.plot.width=6, repr.plot.height=3)
```

In [22]:

```
# check how the numerical features response to loan_status_binary
boxplot(total_acc ~ loan_status_binary, data = loan,xlab='loan_status_binary',ylab=
boxplot(log_tot_coll_amt ~ loan_status_binary, data = loan,xlab='loan_status_binary
boxplot(tot_cur_bal ~ loan_status_binary, data = loan,xlab='loan_status_binary',ylab
boxplot(inq_last_6mths ~ loan_status_binary, data = loan,xlab='loan_status_binary',y
boxplot(open_acc ~ loan_status_binary, data = loan,xlab='loan_status_binary',ylab='
boxplot(log_annual_inc ~ loan_status_binary, data = loan,xlab='loan_status_binary',y
boxplot(total_pymnt ~ loan_status_binary, data = loan,xlab='loan_status_binary',ylab
boxplot(total_rec_int_log ~ loan_status_binary, data = loan,xlab='loan_status_binar
boxplot(log_last_pymnt_amnt ~ loan_status_binary, data = loan,xlab='loan_status_bina
boxplot(int_rate ~ loan_status_binary, data = loan,xlab='loan_status_binary',ylab='
boxplot(total_rec_int_log ~ loan_status_binary, data = loan,xlab='loan_status_binar
```



In [12]:

```
library(MASS)
# compute the chi square value between categorical features with loan_status_binary
chisq.test(table(loan$term, loan$loan_status_binary))
chisq.test(table(loan$home_ownership, loan$loan_status_binary))
chisq.test(table(loan$application_type, loan$loan_status_binary))
chisq.test(table(loan$pymnt_plan, loan$loan_status_binary))
chisq.test(table(loan$state_mean_int, loan$loan_status_binary))
chisq.test(table(loan$emp_length, loan$loan_status_binary))
```

```
	Pearson's Chi-squared test with Yates' continuity correction

data:  table(loan$term, loan$loan_status_binary)
X-squared = 1390.6, df = 1, p-value < 2.2e-16

	Pearson's Chi-squared test

data:  table(loan$home_ownership, loan$loan_status_binary)
X-squared = 1333.6, df = 3, p-value < 2.2e-16

	Pearson's Chi-squared test with Yates' continuity correction

data:  table(loan$application_type, loan$loan_status_binary)
X-squared = 30.979, df = 1, p-value = 2.609e-08

Warning message in chisq.test(table(loan$pymnt_plan, loan$loan_status_
binary)):
“Chi-squared approximation may be incorrect”

	Pearson's Chi-squared test with Yates' continuity correction

data:  table(loan$pymnt_plan, loan$loan_status_binary)
X-squared = 19.923, df = 1, p-value = 8.061e-06

	Pearson's Chi-squared test

data:  table(loan$state_mean_int, loan$loan_status_binary)
X-squared = 150.14, df = 3, p-value < 2.2e-16

	Pearson's Chi-squared test

data:  table(loan$emp_length, loan$loan_status_binary)
X-squared = 512.67, df = 11, p-value < 2.2e-16
```

In [13]:

```
library(glmnet) # can only take matrix
```

```
Loading required package: Matrix
Loading required package: foreach
Warning message:
“package ‘foreach’ was built under R version 3.4.3”Loaded glmnet 2.0-1
3
```

In [14]:

```
# scale (normalize) all the numerical features before doing train / test split.
nums <- sapply(loan, is.numeric)
loan[nums] <- lapply(loan[nums], scale)

summary(loan)
```

```
 mths_since_last_major_derog mths_since_last_delinq  tot_coll_amt
 Min.   :  0.0               Min.   :  0.0          Min.   :      0
 1st Qu.: 27.0               1st Qu.: 15.0          1st Qu.:      0
 Median : 44.0               Median : 31.0          Median :      0
 Mean   : 44.1               Mean   : 34.1          Mean   :    208
 3rd Qu.: 61.0               3rd Qu.: 50.0          3rd Qu.:      0
 Max.   :188.0               Max.   :188.0          Max.   :9152545
 NA's   :665676              NA's   :454312
  tot_cur_bal       total_rev_hi_lim    revol_util
 Min.   :      0   Min.   :      0   Min.   :  0.00
 1st Qu.:  32246   1st Qu.:  13900   1st Qu.: 37.70
 Median :  80559   Median :  23700   Median : 56.00
 Mean   : 134794   Mean   :  32069   Mean   : 55.07
 3rd Qu.: 195794   3rd Qu.:  39800   3rd Qu.: 73.60
 Max.   :8000078   Max.   :9999999   Max.   :892.30
                   NA's   :70276     NA's   :502
 collections_12_mths_ex_med  delinq_2yrs      inq_last_6mths       ope
n_acc
 Min.   : 0.00000           Min.   : 0.0000   Min.   : 0.0000   Min.
```

In [15]:

```
set.seed(1)
train.ind <- sample(1:dim(loan)[1], 0.7 * dim(loan)[1])
train <- loan[train.ind, ]
dim(train)
test <- loan[-train.ind, ]
```

```
621165  64
```

In [16]:

```
# select the numerical/categorical features that are responsive to loan_status_bina
train.sub <- train[, c('loan_status_binary','total_acc', 'tot_cur_bal','inq_last_6mt
                        'int_rate', 'total_pymnt', 'total_rec_int_log', 'log_last_pym
                        'open_acc','log_tot_coll_amt','term', 'home_ownership',  'app
                        'state_mean_int','emp_length')]

test.sub <- test[, c('loan_status_binary','total_acc', 'tot_cur_bal','inq_last_6mths
                      'int_rate', 'total_pymnt', 'total_rec_int_log', 'log_last_pymn
                      'open_acc','log_tot_coll_amt','term', 'home_ownership',  'appl
                    'state_mean_int','emp_length')]
```

In [17]:

```
# convert to matrixes as required by glmnet.
ind <- train.sub[, -1]
ind <- model.matrix(~., ind)

dim(ind)
summary(ind)
dep <- train.sub[, 1]
dep <- as.matrix(dep)
summary(dep)
dim(dep)
typeof(dep)
```

621165 32

```
  (Intercept)   total_acc            tot_cur_bal          inq_last_6mths
 Min.   :1     Min.   :-2.049597   Min.   :-0.908367   Min.   :-0.69569
 1st Qu.:1     1st Qu.:-0.698288   1st Qu.:-0.690787   1st Qu.:-0.69569
 Median :1     Median :-0.107090   Median :-0.365485   Median :-0.69569
 Mean   :1     Mean   : 0.001167   Mean   : 0.000883   Mean   :-0.00137
 3rd Qu.:1     3rd Qu.: 0.568565   3rd Qu.: 0.413477   3rd Qu.: 0.30588
 Max.   :1     Max.   :11.041210   Max.   :31.253584   Max.   :30.35277
   loan_amnt                dti                  int_rate
 Min.   :-1.6899223   Min.   :-2.1844292   Min.   :-1.808987
 1st Qu.:-0.8008180   1st Qu.:-0.7503527   1st Qu.:-0.743231
 Median :-0.2080818   Median :-0.0574165   Median :-0.058591
 Mean   : 0.0000272   Mean   :-0.0004977   Mean   :-0.000683
 3rd Qu.: 0.6217489   3rd Qu.: 0.6993902   3rd Qu.: 0.673973
 Max.   : 2.3999576   Max.   : 3.1011671   Max.   : 3.592820
  total_pymnt         total_rec_int_log   log_last_pymnt_amnt
 Min.   :-0.960309   Min.   :-4.409052   Min.   :-3.890081
 1st Qu.:-0.716842   1st Qu.:-0.432287   1st Qu.:-0.429845
 Median :-0.338710   Median : 0.146676   Median :-0.122226
 Mean   :-0.000091   Mean   : 0.000262   Mean   : 0.000569
 3rd Qu.: 0.389095   3rd Qu.: 0.625063   3rd Qu.: 0.235473
 Max.   : 6.380028   Max.   : 2.158997   Max.   : 2.555184
 log_annual_inc          open_acc         log_tot_coll_amt     term 60 mo
nths
```

```
 Min.   :-6.677380   Min.   :-2.17189   Min.   :-0.375950   Min.   :0.
0000
 1st Qu.:-0.683414   1st Qu.:-0.66735   1st Qu.:-0.375950   1st Qu.:0.
0000
 Median : 0.012670   Median :-0.10315   Median :-0.375950   Median :0.
0000
 Mean   : 0.000566   Mean   : 0.00057   Mean   : 0.000384   Mean   :0.
2997
 3rd Qu.: 0.628682   3rd Qu.: 0.46106   3rd Qu.:-0.375950   3rd Qu.:1.
0000
 Max.   : 9.448524   Max.   :13.24968   Max.   : 5.736659   Max.   :1.
0000
 home_ownershipOTHER home_ownershipOWN home_ownershipRENT application_
typeJOINT
 Min.   :0.0000000   Min.   :0.00000   Min.   :0.0000     Min.   :0.00
00000
 1st Qu.:0.0000000   1st Qu.:0.00000   1st Qu.:0.0000     1st Qu.:0.00
00000
 Median :0.0000000   Median :0.00000   Median :0.0000     Median :0.00
00000
 Mean   :0.0002544   Mean   :0.09876   Mean   :0.4009     Mean   :0.00
06134
 3rd Qu.:0.0000000   3rd Qu.:0.00000   3rd Qu.:1.0000     3rd Qu.:0.00
00000
 Max.   :1.0000000   Max.   :1.00000   Max.   :1.0000     Max.   :1.00
00000
 state_mean_intlow state_mean_intlowmedium state_mean_intmediumhigh
 Min.   :0.00000   Min.   :0.0000          Min.   :0.0000
 1st Qu.:0.00000   1st Qu.:0.0000          1st Qu.:0.0000
 Median :0.00000   Median :1.0000          Median :0.0000
 Mean   :0.08751   Mean   :0.5175          Mean   :0.2654
 3rd Qu.:0.00000   3rd Qu.:1.0000          3rd Qu.:1.0000
 Max.   :1.00000   Max.   :1.0000          Max.   :1.0000
 emp_length1 year  emp_length10+ years emp_length2 years emp_length3 y
ears
 Min.   :0.00000   Min.   :0.0000      Min.   :0.00000   Min.   :0.000
00
 1st Qu.:0.00000   1st Qu.:0.0000      1st Qu.:0.00000   1st Qu.:0.000
00
 Median :0.00000   Median :0.0000      Median :0.00000   Median :0.000
00
 Mean   :0.06412   Mean   :0.3289      Mean   :0.08876   Mean   :0.078
93
 3rd Qu.:0.00000   3rd Qu.:1.0000      3rd Qu.:0.00000   3rd Qu.:0.000
00
 Max.   :1.00000   Max.   :1.0000      Max.   :1.00000   Max.   :1.000
00
 emp_length4 years emp_length5 years emp_length6 years emp_length7 yea
rs
 Min.   :0.00000   Min.   :0.0000    Min.   :0.00000   Min.   :0.00000
 1st Qu.:0.00000   1st Qu.:0.0000    1st Qu.:0.00000   1st Qu.:0.00000
 Median :0.00000   Median :0.0000    Median :0.00000   Median :0.00000
 Mean   :0.05882   Mean   :0.0627    Mean   :0.04861   Mean   :0.05035
 3rd Qu.:0.00000   3rd Qu.:0.0000    3rd Qu.:0.00000   3rd Qu.:0.00000  
 Max.   :1.00000   Max.   :1.0000    Max.   :1.00000   Max.   :1.00000  
 emp_length8 years emp_length9 years emp_lengthn/a    
 Min.   :0.00000   Min.   :0.00000   Min.   :0.00000  
 1st Qu.:0.00000   1st Qu.:0.00000   1st Qu.:0.00000  
 Median :0.00000   Median :0.00000   Median :0.00000  
 Mean   :0.04962   Mean   :0.03891   Mean   :0.05051  
 3rd Qu.:0.00000   3rd Qu.:0.00000   3rd Qu.:0.00000  
 Max.   :1.00000   Max.   :1.00000   Max.   :1.00000  
```

```
 V1      
 0:574004
 1: 47161
```

621165 1

'character'

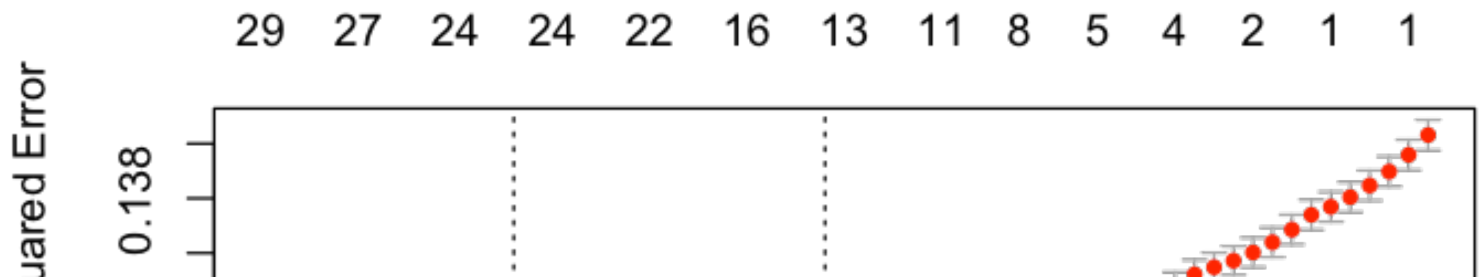
In [18]:

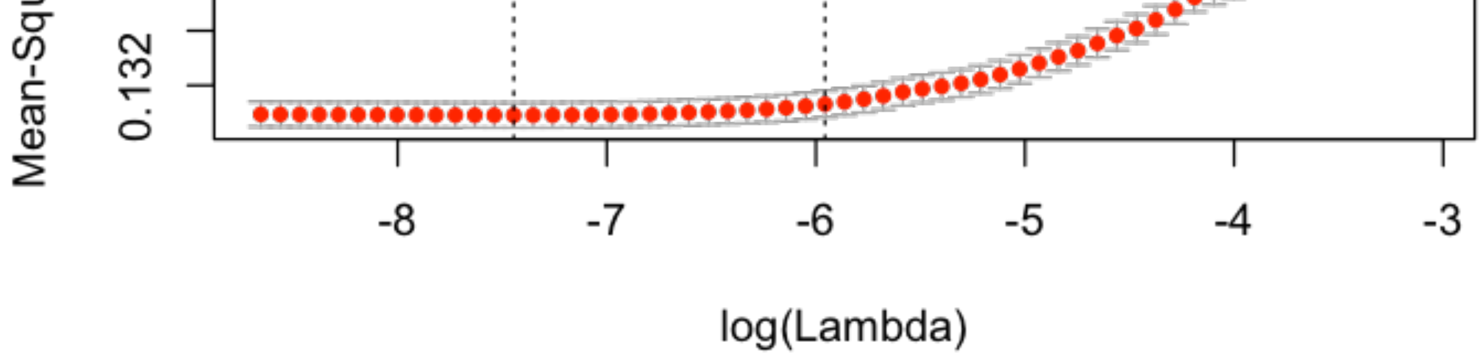
```
# cross-validation with glmnet for logistic regression
cvfit <- cv.glmnet(ind, dep, family = "binomial", type.measure = "mse")
plot(cvfit)
coef(cvfit, s="lambda.min")
coef(cvfit, s="lambda.1se")
```

```
33 x 1 sparse Matrix of class "dgCMatrix"
                                   1
(Intercept)              -2.76725511
(Intercept)               .         
total_acc                 0.05938371
tot_cur_bal              -0.06117577
inq_last_6mths            0.16271536
loan_amnt                 0.28691614
dti                      -0.04946683
int_rate                  0.55755441
total_pymnt              -0.54998352
total_rec_int_log         0.82338753
log_last_pymnt_amnt      -0.87092358
log_annual_inc           -0.11254141
open_acc                 -0.06106200
log_tot_coll_amt         -0.10893522
term 60 months           -0.67964146
home_ownershipOTHER       0.68068415
home_ownershipOWN        -0.05372664
home_ownershipRENT        0.06047789
application_typeJOINT    -0.83170926
state_mean_intlow        -0.07241401
state_mean_intlowmedium   0.01656687
state_mean_intmediumhigh  .         
emp_length1 year          .         
emp_length10+ years      -0.09469249
emp_length2 years         .         
```

```
emp_length3 years         .
emp_length4 years         .
emp_length5 years         0.04940558
emp_length6 years         0.13391433
emp_length7 years         0.03648551
emp_length8 years         .
emp_length9 years         .
emp_lengthn/a            -0.04801034

33 x 1 sparse Matrix of class "dgCMatrix"
                                    1
(Intercept)              -2.718571527
(Intercept)               .
total_acc                 .
tot_cur_bal              -0.034258341
inq_last_6mths            0.135462977
loan_amnt                 0.102038385
dti                       .
int_rate                  0.529893971
total_pymnt              -0.331254575
total_rec_int_log         0.613571692
log_last_pymnt_amnt      -0.686113938
log_annual_inc           -0.040403510
open_acc                 -0.008251434
log_tot_coll_amt         -0.069412048
term 60 months           -0.395110780
home_ownershipOTHER       .
home_ownershipOWN         .
home_ownershipRENT        0.045449241
application_typeJOINT     .
state_mean_intlow         .
state_mean_intlowmedium   .
state_mean_intmediumhigh  .
emp_length1 year          .
emp_length10+ years      -0.052798159
emp_length2 years         .
emp_length3 years         .
emp_length4 years         .
emp_length5 years         .
emp_length6 years         0.003031634
emp_length7 years         .
emp_length8 years         .
emp_length9 years         .
emp_lengthn/a             .
```





In [21]:

```
# apply the model with cvfit$lambda.min to test data
ind_test <- test.sub[, -1]
x_test <- model.matrix(~.,ind_test)
dep_test <- test.sub[, 1]
y_test <- as.matrix(dep_test)
#predict class, type="class"
lasso_prob <- predict(cvfit,newx = x_test,s=cvfit$lambda.min,type="response")
#translate probabilities to predictions
lasso_predict <- rep("neg",nrow(ind_test))
lasso_predict[lasso_prob>.5] <- "pos"
#confusion matrix
table(pred=lasso_predict,true=test.sub$loan_status_binary)
```

```
     true
pred       0      1
  neg 245732  20124
  pos    214    144
```

In [ ]:

In [ ]: