[TYPE THE COMPANY NAME]

20-PBD-002
Shraddha P Jain

End Semester Assignment
3803(B)-MOM

The dataset *ESE 2*is ahealthcare dataset which has 14635 observations with several attributes. The objective is to builda model that predicts the presence of complications of surgery of the patient. The data description is given in sheet 2 of excel sheet.

Preprocessing codes:

```
library(xlsx)
data.2 = read.xlsx("C:\\Users\\Shraddha\\Downloads\\ESE2_002.xlsx",sheetIndex
= 1)

dim(data.2)
str(data.2)
#checking for NA
lapply(data.2,function(x) { length(which(is.na(x)))})
```

```
Console  Terminal
~/
>
> lapply(data.2,function(x) { length(which(is.na(x)))})
$bmi_002
[1] 0

$Age_002
[1] 0

$asa_status_002
[1] 0

$ahrq_ccs_002
[1] 0

$ccsComplicationRate_002
[1] 0

$ccsMort30Rate_002
[1] 0

$complication_rsi_002
[1] 0

$dow_002
[1] 0

$gender_002
[1] 0

$hour_002
[1] 0

$month_002
[1] 0

$moonphase_002
```

```
$moonphase_002
[1] 0

$mort30_002
[1] 0

$mortality_rsi_002
[1] 0

$race_002
[1] 0

$complication_002
[1] 0

>
```

```
# converting into factor
data.2$asa_status_002 = as.factor(data.2$asa_status_002)
data.2$gender_002 = as.factor(data.2$gender_002)
```

```
data.2$dow_002 = as.factor(data.2$dow_002)
data.2$month_002 = as.factor(data.2$month_002)
data.2$moonphase_002 = as.factor(data.2$moonphase_002)
data.2$mort30_002 = as.factor(data.2$mort30_002)
data.2$race_002 = as.factor(data.2$race_002)
data.2$complication_002 = as.factor(data.2$complication_002)
```

Answer the following questions.

a) Obtain the proportion of patients who had complications based on asa_status. Which among these seems to have an indication of post-surgery complication according to the given data? Justify your answer.

Ans:

```
tabl.2 =table(data.2$asa_status_002,data.2$complication_002)
prop.table(tabl.2,margin = 1)
```

```
> tabl.2 =table(data.2$asa_status_002,data.2$complication_002)
> prop.table(tabl.2,margin = 1)

           0         1
  1 0.7295716 0.2704284
  2 0.7711561 0.2288439
  3 0.5416667 0.4583333
>
```

Interpretation: Above is the table of proportions of people who have complications based on their asa status. Around 27% of patients who had asa status as 1 had complications, as compared to 23% of patients with asa status as 2, and 45% of patients with asa status 3.

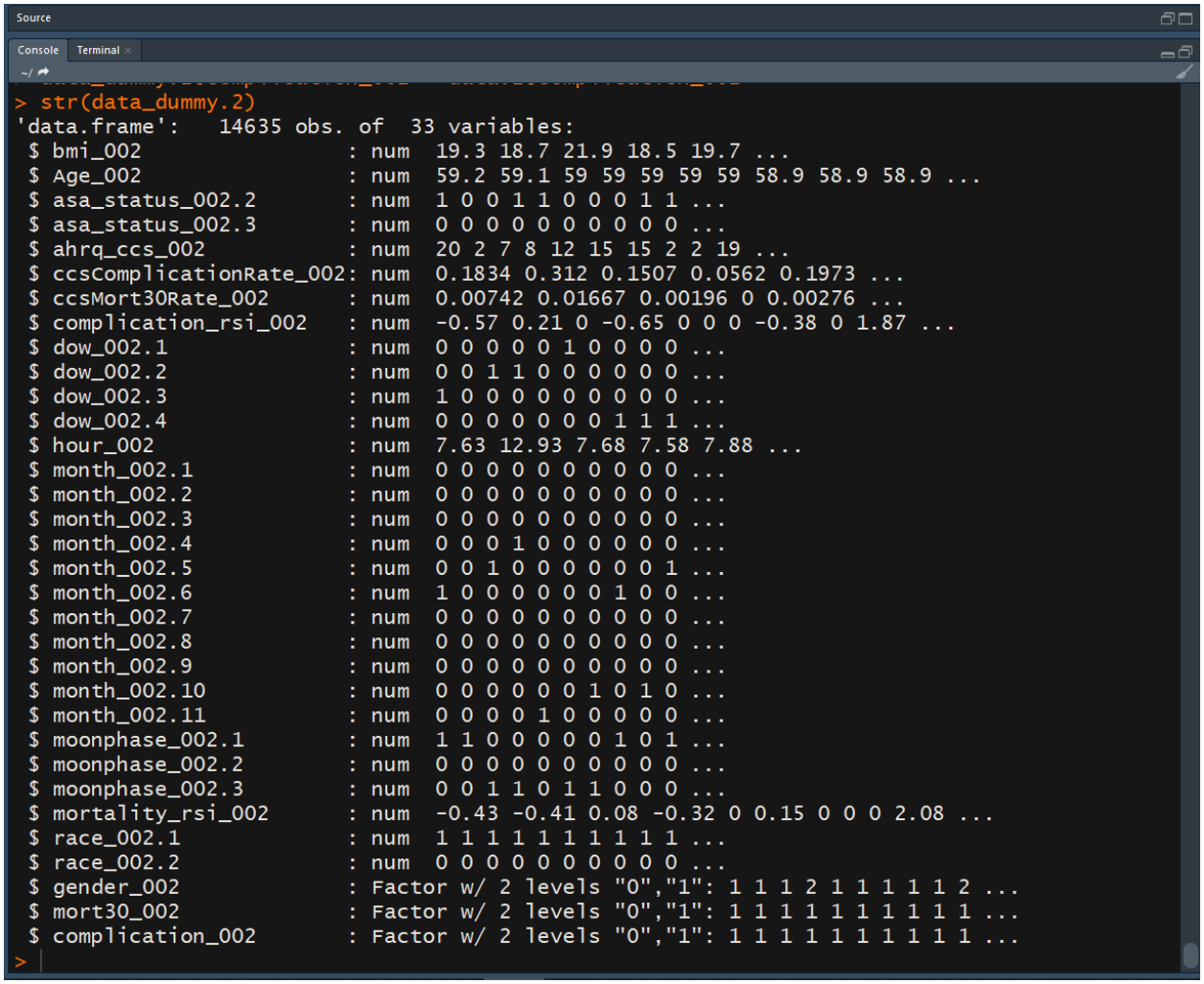
Ans: Patients with asa status 3 seem to have a higher risk of complication during surgery as compared to others. This can be justified by the above table, as they 45% of patients with asa status 3 had face complications while for patients with asa status 1 or 2, the proportion of complications in surgeries was 27% and 23% respectively

(b)Logistic regression model

Preprocessing

Creating dummy variables from factors

```
library(caret)
str(data.2)
dummy.2 <- dummyVars(" ~ .-complication_002-gender_002-mort30_002", data = data.2, fullRank = T)
data_dummy.2 <- data.frame(predict(dummy.2, newdata = data.2))
data_dummy.2$gender_002 = data.2$gender_002
data_dummy.2$complication_002 = data.2$complication_002
data_dummy.2$mort30_002 = data.2$mort30_002
```



train test split

```
smp_size.2<-floor(0.7*nrow(data_dummy.2))
```

```
set.seed(1024)
trainingdata.2 <- sample(seq_len(nrow(data_dummy.2)),size=smp_size.2)
training.2<-data_dummy.2[trainingdata.2,]
testing.2<-data_dummy.2[-trainingdata.2,]
```

i. Build a binary logistic regression model to predict the probability of having complications of surgery of the patient based on the predictors. Comment on the overall model significance.

Ans:

```
model.2 = glm(complication_002~.,data = training.2,family = 'binomial')
summary(model)
```

```
> summary(model.2)

Call:
glm(formula = complication_002 ~ ., family = "binomial", data = training.2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.9069  -0.6875  -0.3404   0.1825   2.8170

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)             -2.033370   0.257092  -7.909 2.59e-15 ***
bmi_002                 -0.042194   0.003698 -11.409  < 2e-16 ***
Age_002                  0.018374   0.002138   8.592  < 2e-16 ***
asa_status_002.2         0.257168   0.062273   4.130 3.63e-05 ***
asa_status_002.3         0.490136   0.157070   3.120 0.001805 **
ahrq_ccs_002            -0.009026   0.004870  -1.854 0.063808 .
ccsComplicationRate_002  8.461334   0.510662  16.569  < 2e-16 ***
ccsMort30Rate_002       -38.765141   9.087470  -4.266 1.99e-05 ***
complication_rsi_002     0.345559   0.035328   9.781  < 2e-16 ***
dow_002.1                0.354814   0.084488   4.200 2.67e-05 ***
dow_002.2                0.314098   0.089677   3.503 0.000461 ***
dow_002.3                0.255033   0.085792   2.973 0.002952 **
dow_002.4                0.357683   0.085715   4.173 3.01e-05 ***
hour_002                -0.010160   0.009588  -1.060 0.289279
month_002.1              0.224008   0.125450   1.786 0.074158 .
month_002.2              0.285296   0.145473   1.961 0.049861 *
month_002.3              0.212453   0.131319   1.618 0.105698
month_002.4              0.360886   0.124434   2.900 0.003729 **
month_002.5             -0.020953   0.135196  -0.155 0.876833
month_002.6              0.169563   0.124292   1.364 0.172496
month_002.7             -0.032883   0.133106  -0.247 0.804877
month_002.8             -0.873545   0.129832  -6.728 1.72e-11 ***
month_002.9              0.005057   0.139181   0.036 0.971018
month_002.10             0.331476   0.135334   2.449 0.014313 *
```

```
Console  Terminal
~/
dow_002.1                0.354814   0.084488   4.200 2.67e-05 ***
dow_002.2                0.314098   0.089677   3.503 0.000461 ***
dow_002.3                0.255033   0.085792   2.973 0.002952 **
dow_002.4                0.357683   0.085715   4.173 3.01e-05 ***
hour_002                -0.010160   0.009588  -1.060 0.289279
month_002.1              0.224008   0.125450   1.786 0.074158 .
month_002.2              0.285296   0.145473   1.961 0.049861 *
month_002.3              0.212453   0.131319   1.618 0.105698
month_002.4              0.360886   0.124434   2.900 0.003729 **
month_002.5             -0.020953   0.135196  -0.155 0.876833
month_002.6              0.169563   0.124292   1.364 0.172496
month_002.7             -0.032883   0.133106  -0.247 0.804877
month_002.8             -0.873545   0.129832  -6.728 1.72e-11 ***
month_002.9              0.005057   0.139181   0.036 0.971018
month_002.10             0.331476   0.135334   2.449 0.014313 *
month_002.11             0.150129   0.130313   1.152 0.249296
moonphase_002.1          0.499557   0.076991   6.489 8.67e-11 ***
moonphase_002.2          0.346942   0.078200   4.437 9.14e-06 ***
moonphase_002.3          0.448983   0.077991   5.757 8.57e-09 ***
mortality_rsi_002        0.237648   0.038768   6.130 8.79e-10 ***
race_002.1              -0.119049   0.083829  -1.420 0.155565
race_002.2               0.074441   0.158586   0.469 0.638780
gender_0021              0.051754   0.055851   0.927 0.354110
mort30_0021             -0.963737   0.443096  -2.175 0.029630 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 11554.0  on 10243  degrees of freedom
Residual deviance:  8831.9  on 10211  degrees of freedom
AIC: 8897.9

Number of Fisher Scoring iterations: 5
```

with(model.2,pchisq(null.deviance-deviance,df.null-df.residual,lower.tail = F))

```
> with(model.2,pchisq(null.deviance-deviance,df.null-df.residual,lower.tail = F))
[1] 0
```

Comment: Above I have built a logistic regression model to predict the probability of having complication in surgery using all available predictors.
The model is overall significant, but there are many variables that are not significant

ii. Find out and report which variables are statistically significant in the logistic regression model built in (i).

```
> anova(model.2,test = 'Chisq')
Analysis of Deviance Table

Model: binomial, link: logit

Response: complication_002

Terms added sequentially (first to last)


                        Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                                    10243    11554.0
bmi_002                  1   270.02     10242    11283.9 < 2.2e-16 ***
Age_002                  1   157.66     10241    11126.3 < 2.2e-16 ***
asa_status_002.2         1    13.52     10240    11112.8 0.0002359 ***
asa_status_002.3         1   127.59     10239    10985.2 < 2.2e-16 ***
ahrq_ccs_002             1    76.55     10238    10908.6 < 2.2e-16 ***
ccsComplicationRate_002  1  1179.28     10237     9729.3 < 2.2e-16 ***
ccsMort30Rate_002        1     8.47     10236     9720.9 0.0036076 **
complication_rsi_002     1   486.35     10235     9234.5 < 2.2e-16 ***
dow_002.1                1    12.40     10234     9222.1 0.0004295 ***
dow_002.2                1     8.59     10233     9213.5 0.0033788 **
dow_002.3                1    11.42     10232     9202.1 0.0007267 ***
dow_002.4                1    60.93     10231     9141.2 5.905e-15 ***
hour_002                 1     0.00     10230     9141.2 0.9508225
month_002.1              1     5.40     10229     9135.8 0.0200807 *
month_002.2              1     5.15     10228     9130.6 0.0232690 *
month_002.3              1     6.88     10227     9123.7 0.0086986 **
month_002.4              1    23.12     10226     9100.6 1.524e-06 ***
month_002.5              1     0.70     10225     9099.9 0.4040287
month_002.6              1    12.09     10224     9087.8 0.0005074 ***
month_002.7              1     2.12     10223     9085.7 0.1457842
month_002.8              1   144.01     10222     8941.7 < 2.2e-16 ***
```

```
month_002.6              1    12.09     10224     9087.8 0.0005074 ***
month_002.7              1     2.12     10223     9085.7 0.1457842
month_002.8              1   144.01     10222     8941.7 < 2.2e-16 ***
month_002.9              1     1.29     10221     8940.4 0.2552987
month_002.10             1     3.83     10220     8936.6 0.0504522 .
month_002.11             1     1.43     10219     8935.2 0.2313182
moonphase_002.1          1    14.14     10218     8921.0 0.0001695 ***
moonphase_002.2          1     4.01     10217     8917.0 0.0453531 *
moonphase_002.3          1    36.19     10216     8880.8 1.787e-09 ***
mortality_rsi_002        1    40.08     10215     8840.7 2.444e-10 ***
race_002.1               1     3.17     10214     8837.6 0.0750708 .
race_002.2               1     0.21     10213     8837.4 0.6473235
gender_002               1     0.83     10212     8836.5 0.3609002
mort30_002               1     4.61     10211     8831.9 0.0318381 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
>
```

Interpretation: Above, we can see the significance of all the variables used. All the variables with p value of chi square less than .05 are significant predictors. These include:

```
"bmi_002"                "Age_002"                "asa_status_002.2"
"asa_status_002.3"       "ahrq_ccs_002"           "ccsComplicationRate_002"
"ccsMort30Rate_002"      "complication_rsi_002"   "dow_002.1"
"dow_002.2"              "dow_002.3"              "dow_002.4"
"month_002.1"            "month_002.2"           "month_002.3"
"month_002.4"            "month_002.6"            "month_002.8"
"month_002.10"           "moonphase_002.1"        "moonphase_002.2"
"moonphase_002.3"       "mortality_rsi_002"      "race_002.1"
"mort30_002"             "complication_002"
```

iii. Build a new logistic regression model using only significant features.Report the model diagnostics followed to build this model.

Ans: model_step = step(glm(complication_002~.,data = dat_transformed,family = 'binomial'))
summary(model_step)

```
> summary(model_step)

Call:
glm(formula = complication_002 ~ bmi_002 + Age_002 + asa_status_002.2 +
    asa_status_002.3 + ahrq_ccs_002 + ccsComplicationRate_002 +
    ccsMort30Rate_002 + complication_rsi_002 + dow_002.1 + dow_002.2 +
    dow_002.3 + dow_002.4 + month_002.1 + month_002.2 + month_002.3 +
    month_002.4 + month_002.6 + month_002.8 + month_002.10 +
    month_002.11 + moonphase_002.1 + moonphase_002.2 + moonphase_002.3 +
    mortality_rsi_002 + race_002.1 + mort30_002, family = "binomial",
    data = training.2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.9232  -0.6885  -0.3436   0.1816   2.8108

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)             -2.110686   0.219370  -9.622  < 2e-16 ***
bmi_002                 -0.042767   0.003663 -11.676  < 2e-16 ***
Age_002                  0.018635   0.002126   8.764  < 2e-16 ***
asa_status_002.2         0.257535   0.062139   4.144 3.41e-05 ***
asa_status_002.3         0.492806   0.156822   3.142 0.001675 **
ahrq_ccs_002            -0.008598   0.004853  -1.772 0.076455 .
ccsComplicationRate_002  8.476753   0.510498  16.605  < 2e-16 ***
ccsMort30Rate_002       -38.903459   9.078289  -4.285 1.82e-05 ***
complication_rsi_002     0.345240   0.035289   9.783  < 2e-16 ***
dow_002.1                0.349187   0.084305   4.142 3.44e-05 ***
dow_002.2                0.311692   0.089585   3.479 0.000503 ***
dow_002.3                0.252100   0.085682   2.942 0.003258 **
dow_002.4                0.346854   0.085199   4.071 4.68e-05 ***
month_002.1              0.233528   0.098919   2.361 0.018236 *
```

```
dow_002.3                0.232100   0.083682   2.942 0.003258 **
dow_002.4                0.346854   0.085199   4.071 4.68e-05 ***
month_002.1              0.233528   0.098919   2.361 0.018236 *
month_002.2              0.293475   0.123197   2.382 0.017212 *
month_002.3              0.227498   0.106278   2.141 0.032307 *
month_002.4              0.373481   0.097635   3.825 0.000131 ***
month_002.6              0.183399   0.097486   1.881 0.059933 .
month_002.8             -0.854846   0.104594  -8.173 3.01e-16 ***
month_002.10             0.340094   0.111042   3.063 0.002193 **
month_002.11             0.158346   0.104869   1.510 0.131057
moonphase_002.1          0.494006   0.076830   6.430 1.28e-10 ***
moonphase_002.2          0.341194   0.078010   4.374 1.22e-05 ***
moonphase_002.3          0.445326   0.077776   5.726 1.03e-08 ***
mortality_rsi_002        0.231919   0.038572   6.013 1.83e-09 ***
race_002.1              -0.132170   0.074275  -1.779 0.075164 .
mort30_0021             -0.961468   0.442614  -2.172 0.029837 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 11554.0  on 10243  degrees of freedom
Residual deviance:  8834.3  on 10217  degrees of freedom
AIC: 8888.3

Number of Fisher Scoring iterations: 5

>
```

The model diagonostic used for this is AIC.

iv. Write an estimated logistic regression model obtained in (iii)

Ans: The estimated logistic regression model is:

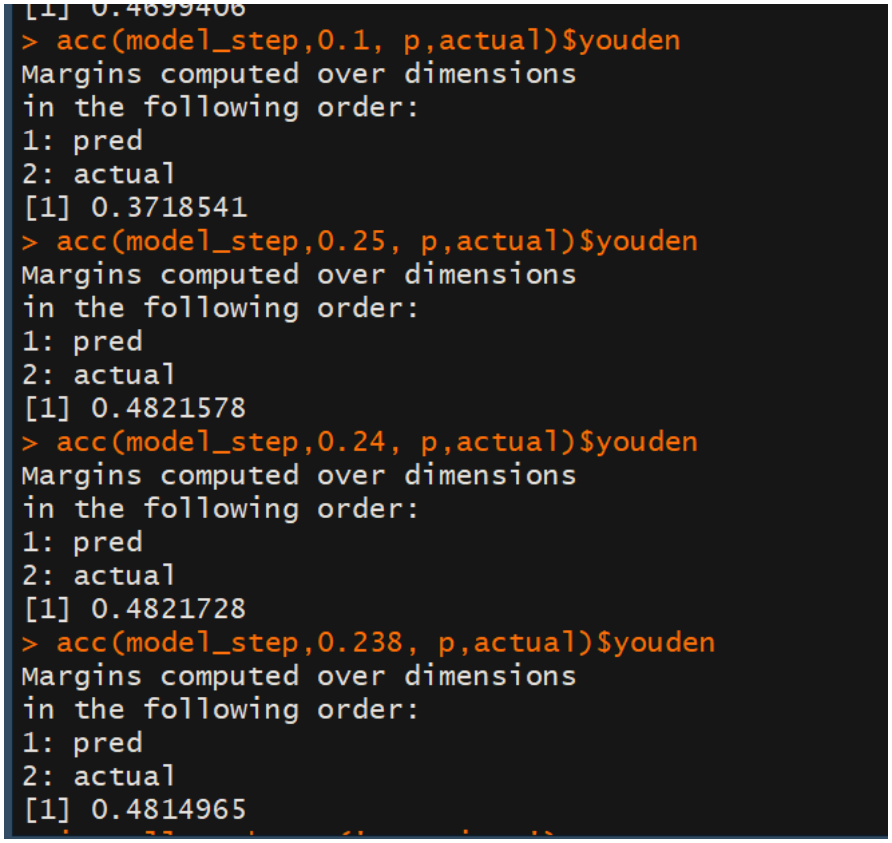
$$p = \frac{1}{1 + e^{-2.11 - .0427 * bmi + 0.186 * Age + 0.25 * asa\_Status1}}$$

(similarly all the variables will be added)

v. Use Youden's index to find the most optimal cut-off probability value for the best model chosen in (iii).

```
p = predict(model_step,type = 'response')
p

actual = training.2$complication_002
```

```
#function to calculate accuracy metrics and youden index
acc <- function(mod, pp, p,actual) {
  out = c()
  ## Classification table
  pred <- ifelse(p<pp,0,1)
#  pred_test <- ifelse(p_test<pp,0,1)
  tab<- table(pred,actual = actual)
  out$sumtab<- addmargins(tab,FUN=sum)


  TAP <- sum(tab[,2])   #Total actual positives
  TAN <- sum(tab[,1])   # Total actual negatives

  TP <- out$sumtab[2,2]
  TN <- out$sumtab[1,1]
  FP <- out$sumtab[2,1]
  FN <- out$sumtab[1,2]
  out$TPR = TP/TAP  # Sensitivity or recall ## ability to correctly classify
  out$FPR = FP/TAN
  out$TNR = TN/TAN   # Specificity
  out$FNR = FN/TAP
  out$accuracy = (TP+TN)/(TAN+TAP)
  out$miss_classification_error = 1-out$accuracy

  out$precision = TP/(TP+FP)
  # conditional probability of being positive when predicted positive
  out$specificity <- TN/TAN
  out$f_score = TP/(TP+0.5*(FP+FN))
  out$cut_off = pp
  out$youden = out$TPR+out$TNR-1
  return(out)
}
acc(model_step,0.5, p,actual)$youden
acc(model_step,0.4, p,actual)$youden
acc(model_step,0.3, p,actual)$youden
acc(model_step,0.2, p,actual)$youden
acc(model_step,0.1, p,actual)$youden
acc(model_step,0.25, p,actual)$youden
acc(model_step,0.24, p,actual)$youden
acc(model_step,0.238, p,actual)$youden
```



The optimal youden index was found to be at cut off 0.24, with its max value 0.4831728

(c)Decision tree classifier model

# normalizing the variables
attach(data_dummy.2)
Age_002 = (Age_002 - mean(Age_002))/sd(Age_002)
bmi_002= (bmi_002 - mean(bmi_002))/sd(bmi_002)
ccsComplicationRate_002= (ccsComplicationRate_002-
mean(ccsComplicationRate_002))/sd(ccsComplicationRate_002)
ccsMort30Rate_002= (ccsMort30Rate_002 -
mean(ccsMort30Rate_002))/sd(ccsMort30Rate_002)
complication_rsi_002= (complication_rsi_002-
mean(complication_rsi_002))/sd(complication_rsi_002)
detach(data_dummy.2)

Test Train split

```
smp_size.2<-floor(0.7*nrow(data_dummy.2))
set.seed(1024)
trainingdata.2 <- sample(seq_len(nrow(data_dummy.2)),size=smp_size.2)
training.2<-data_dummy.2[trainingdata.2,]
testing.2<-data_dummy.2[-trainingdata.2,]
```

i. Build Random Forest decision tree and clearly identify and report predictor which is classifying the patient having complications of post-surgery.

```
Ranfor= randomForest(complication_002~., data = training.2)
summary(Ranfor)
print(Ranfor)
```

```
> Randomforest_002= randomForest(complication_002~., data = training.2)
> print(Randomforest_002)

Call:
 randomForest(formula = complication_002 ~ ., data = training.2)
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 5

        OOB estimate of  error rate: 13.98%
Confusion matrix:
     0    1 class.error
0 7347  321  0.04186228
1 1111 1465  0.43128882
```

Above is the random forest model.

Below are the variables used for the decision tree

```
> importance(Randomforest_002)
                          MeanDecreaseGini
bmi_002                         394.894808
Age_002                         781.092919
asa_status_002.2                 49.143322
asa_status_002.3                 16.065613
ahrq_ccs_002                    145.570857
ccsComplicationRate_002         298.188442
ccsMort30Rate_002               169.666706
complication_rsi_002            472.678302
dow_002.1                        36.267476
dow_002.2                        32.733013
dow_002.3                        35.530217
dow_002.4                        35.369240
hour_002                        282.145923
month_002.1                      28.377854
month_002.2                      25.256290
month_002.3                      25.136139
month_002.4                      30.089250
month_002.5                      23.310302
month_002.6                      29.334994
month_002.7                      25.858633
month_002.8                      53.760218
month_002.9                      23.218827
month_002.10                     23.159694
month_002.11                     26.244929
moonphase_002.1                  42.066888
moonphase_002.2                  38.229533
moonphase_002.3                  39.839525
mortality_rsi_002               447.707413
race_002.1                       34.279643
race_002.2                       15.291180
gender_002                       39.974885
mort30_002                        2.800705
```

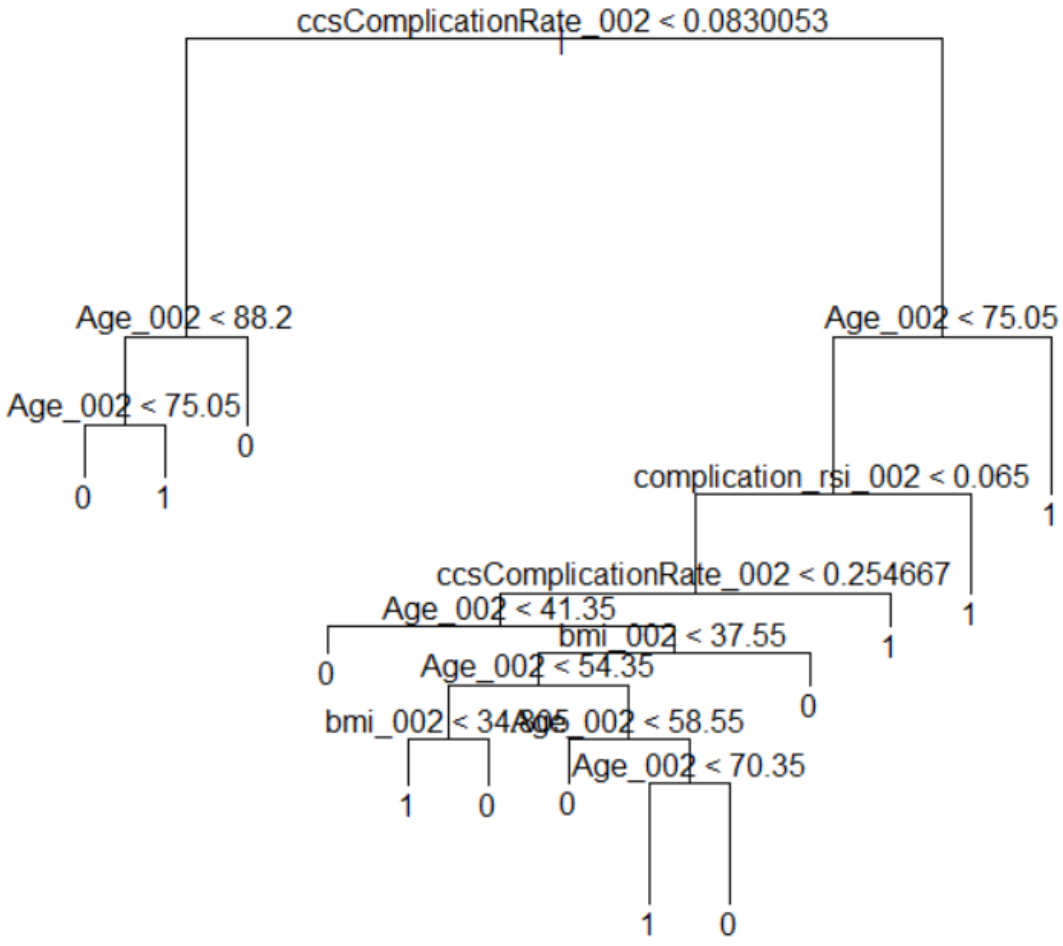
ii. Also plot that decision tree and report the most important splitting criteria (rule).

treemod.2= tree(training.2$complication_002~., data=training.2)

summary(treemod.2)

plot (treemod.2)
text(treemod.2,pretty=0)

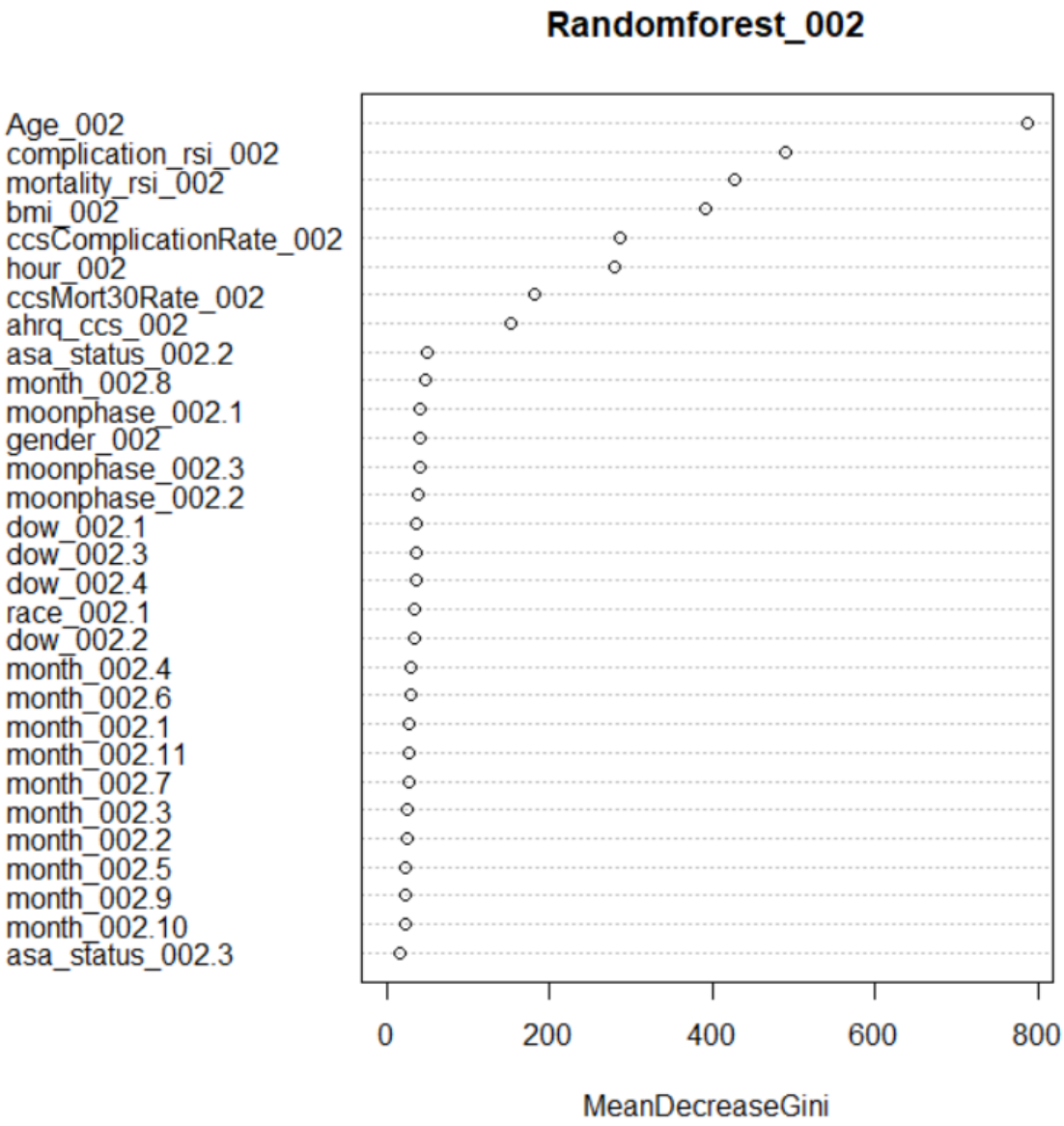
```
Classification tree:
tree(formula = training.2$complication_002 ~ ., data = training.2)
Variables actually used in tree construction:
[1] "ccsComplicationRate_002" "Age_002"                 "complication_rsi_002"
[4] "bmi_002"
Number of terminal nodes:  13
Residual mean deviance:  0.6515 = 6666 / 10230
Misclassification error rate: 0.1393 = 1427 / 10244
```



The most important splitting criteria is whether the cssComplilation rate is <0.083003 or not.

iii. Use variance importance plot, report the variables which are classifying the surgery complication.

varImpPlot(Randomforest_002)



The important variables for classifying are age, complication_rsi, mortality_rsi, bmi, ccsComplicationRate, hour, cssMort30Rate and ahrq_ccs.

(d) Compare the logistic regression model and decision tree classifier performance using confusion matrix with specific accuracy measures or ROC and AUC?

```
acc <- function(mod, pp, p,actual) {
  out = c()
  ## Classification table
  pred <- ifelse(p<pp,0,1)
#  pred_test <- ifelse(p_test<pp,0,1)
  tab<- table(pred,actual = actual)
  out$sumtab<- addmargins(tab,FUN=sum)


  TAP <- sum(tab[,2])   #Total actual positives
  TAN <- sum(tab[,1])   # Total actual negatives

  TP <- out$sumtab[2,2]
  TN <- out$sumtab[1,1]
  FP <- out$sumtab[2,1]
  FN <- out$sumtab[1,2]
  out$TPR = TP/TAP  # Sensitivity or recall ## ability to correctly classify
  out$FPR = FP/TAN
  out$TNR = TN/TAN   # Specificity
  out$FNR = FN/TAP
  out$accuracy = (TP+TN)/(TAN+TAP)
  out$miss_classification_error = 1-out$accuracy

  out$precision = TP/(TP+FP)
  # conditional probability of being positive when predicted positive
  out$specificity <- TN/TAN
  out$f_score = TP/(TP+0.5*(FP+FN))
  out$cut_off = pp
  out$youden = out$TPR+out$TNR-1
  return(out)
}
# Accuracy of logistic regression, with cut off probability = 0.24
acc(model_step,0.24, p,actual)
```

```
p = predict(model_step,type = 'response',newdata = testing.2)
p

actual = testing.2$complication_002
```

```
> acc(model_step,0.24, p,actual)
Margins computed over dimensions
in the following order:
1: pred
2: actual
$sumtab
      actual
pred     0    1  sum
  0   2292  275 2567
  1    985  839 1824
  sum 3277 1114 4391

$TPR
[1] 0.7531418

$FPR
[1] 0.3005798

$TNR
[1] 0.6994202

$FNR
[1] 0.2468582

$accuracy
[1] 0.7130494

$miss_classification_error
[1] 0.2869506

$precision
[1] 0.4599781

$specificity
[1] 0.6994202
```

```
$accuracy
[1] 0.7130494

$miss_classification_error
[1] 0.2869506

$precision
[1] 0.4599781

$specificity
[1] 0.6994202

$f_score
[1] 0.5711368

$cut_off
[1] 0.24

$youden
[1] 0.452562
```

```
# accuracy of random forest
p_random = predict(Randomforest_002,type = 'response',newdata = testing.2)
actual = testing.2$complication_002
acc <- function(mod, p,actual) {
  out = c()
  ## Classification table
  #pred <- ifelse(p<pp,0,1)
  pred = p
#  pred_test <- ifelse(p_test<pp,0,1)
  tab<- table(pred,actual = actual)
  out$sumtab<- addmargins(tab,FUN=sum)


  TAP <- sum(tab[,2])   #Total actual positives
  TAN <- sum(tab[,1])   # Total actual negatives
```

```
  TP <- out$sumtab[2,2]
  TN <- out$sumtab[1,1]
  FP <- out$sumtab[2,1]
  FN <- out$sumtab[1,2]
  out$TPR = TP/TAP  # Sensitivity or recall ## ability to correctly classify
  out$FPR = FP/TAN
  out$TNR = TN/TAN   # Specificity
  out$FNR = FN/TAP
  out$accuracy = (TP+TN)/(TAN+TAP)
  out$miss_classification_error = 1-out$accuracy

  out$precision = TP/(TP+FP)
  # conditional probability of being positive when predicted positive
  out$specificity <- TN/TAN
  out$f_score = TP/(TP+0.5*(FP+FN))
  #out$cut_off = pp
  out$youden = out$TPR+out$TNR-1
  return(out)
}
```

```
> acc(Randomforest_002,p= p_random,actual)
Margins computed over dimensions
in the following order:
1: pred
2: actual
$sumtab
     actual
pred     0    1  sum
  0   3103  486 3589
  1    174  628  802
  sum 3277 1114 4391

$TPR
[1] 0.5637343

$FPR
[1] 0.05309735

$TNR
[1] 0.9469027

$FNR
[1] 0.4362657

$accuracy
[1] 0.8496926

$miss_classification_error
[1] 0.1503074

$precision
[1] 0.7830424

$specificity
[1] 0.9469027
```

```
$miss_classification_error
[1] 0.1503074

$precision
[1] 0.7830424

$specificity
[1] 0.9469027

$f_score
[1] 0.6555324

$youden
[1] 0.5106369
```