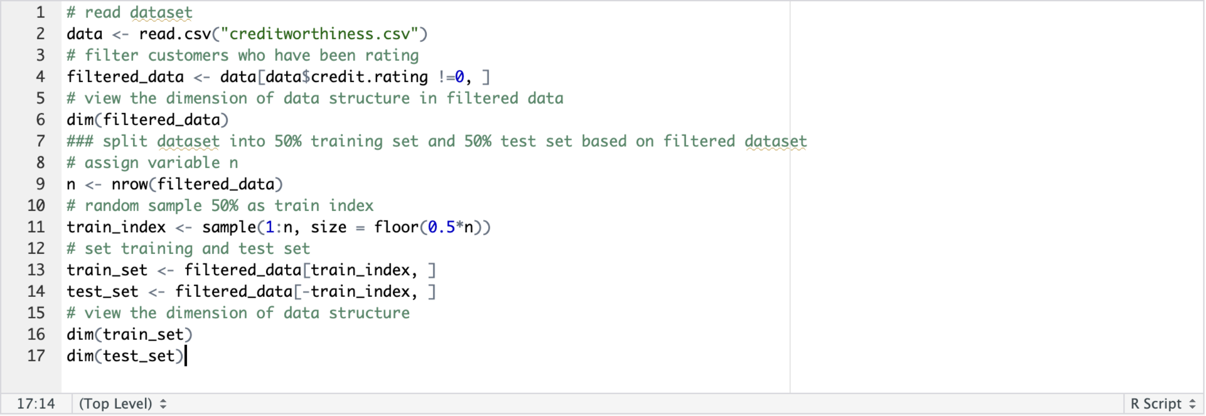
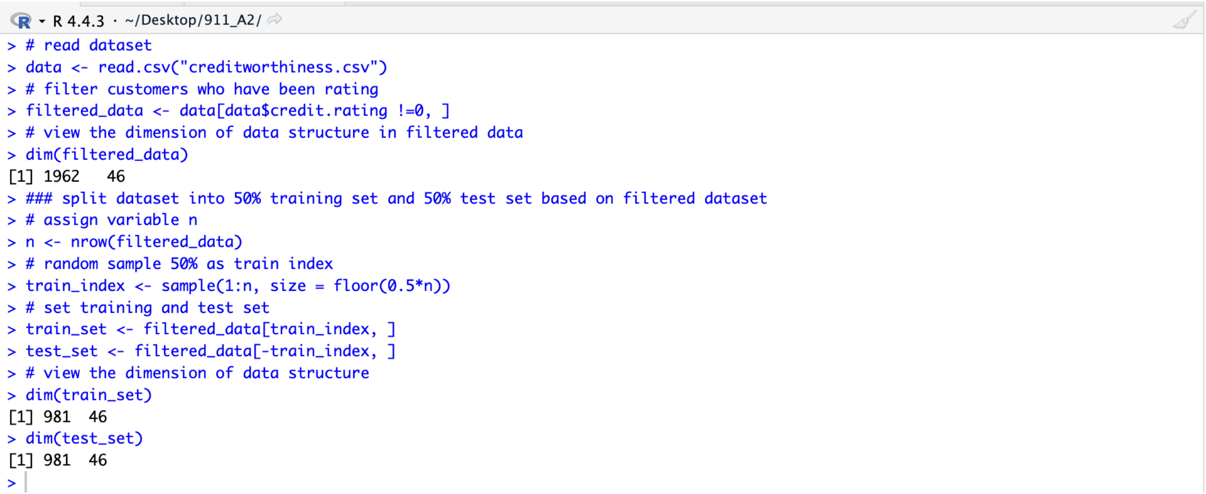
Credit Risk Intelligence Predictive Modeling and Algorithm Benchmarking

1. Data Preprocessing and Train Test Split



```r
# read dataset
data <- read.csv("creditworthiness.csv")
# filter customers who have been rating
filtered_data <- data[data$credit.rating !=0, ]
# view the dimension of data structure in filtered data
dim(filtered_data)
### split dataset into 50% training set and 50% test set based on filtered dataset
# assign variable n
n <- nrow(filtered_data)
# random sample 50% as train index
train_index <- sample(1:n, size = floor(0.5*n))
# set training and test set
train_set <- filtered_data[train_index, ]
test_set <- filtered_data[-train_index, ]
# view the dimension of data structure
dim(train_set)
dim(test_set)
```

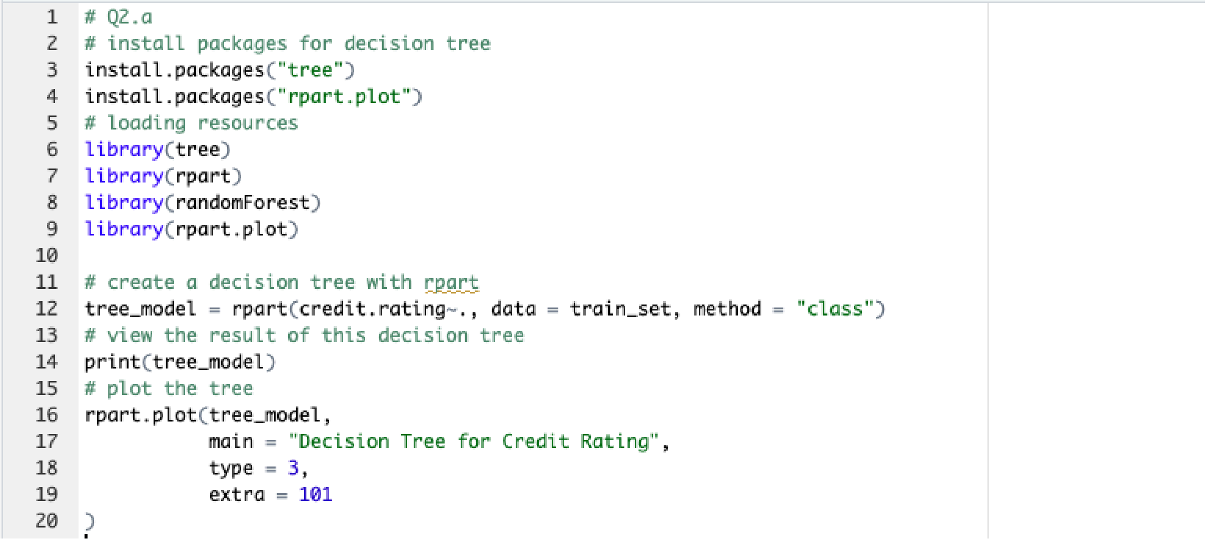


```
> # read dataset
> data <- read.csv("creditworthiness.csv")
> # filter customers who have been rating
> filtered_data <- data[data$credit.rating !=0, ]
> # view the dimension of data structure in filtered data
> dim(filtered_data)
[1] 1962   46
> ### split dataset into 50% training set and 50% test set based on filtered dataset
> # assign variable n
> n <- nrow(filtered_data)
> # random sample 50% as train index
> train_index <- sample(1:n, size = floor(0.5*n))
> # set training and test set
> train_set <- filtered_data[train_index, ]
> test_set <- filtered_data[-train_index, ]
> # view the dimension of data structure
> dim(train_set)
[1] 981  46
> dim(test_set)
[1] 981  46
> 
```

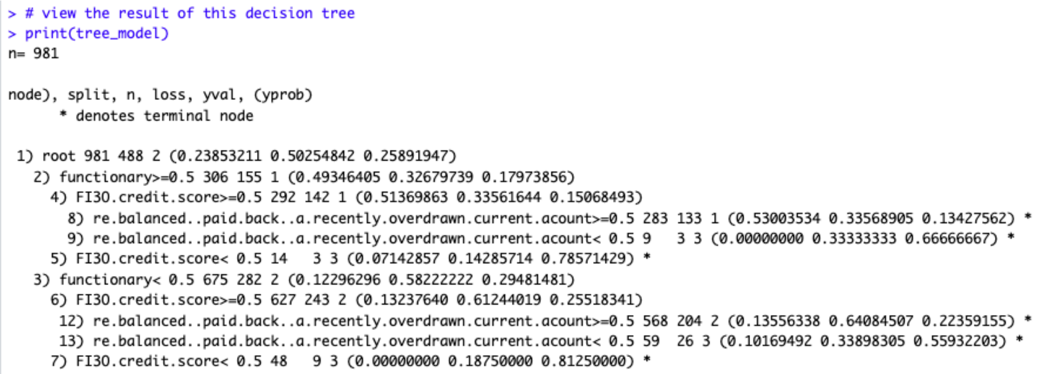
In this task, entries with unknown credit ratings were excluded, resulting in a filtered dataset with 1962 rows and 46 variables. The dataset was randomly split into a training set and a test set by selecting 50% of the rows using randomly sampled indices. Each subset contains 981 rows and 46 columns.

2. Random Forest Optimization and Tree Analysis

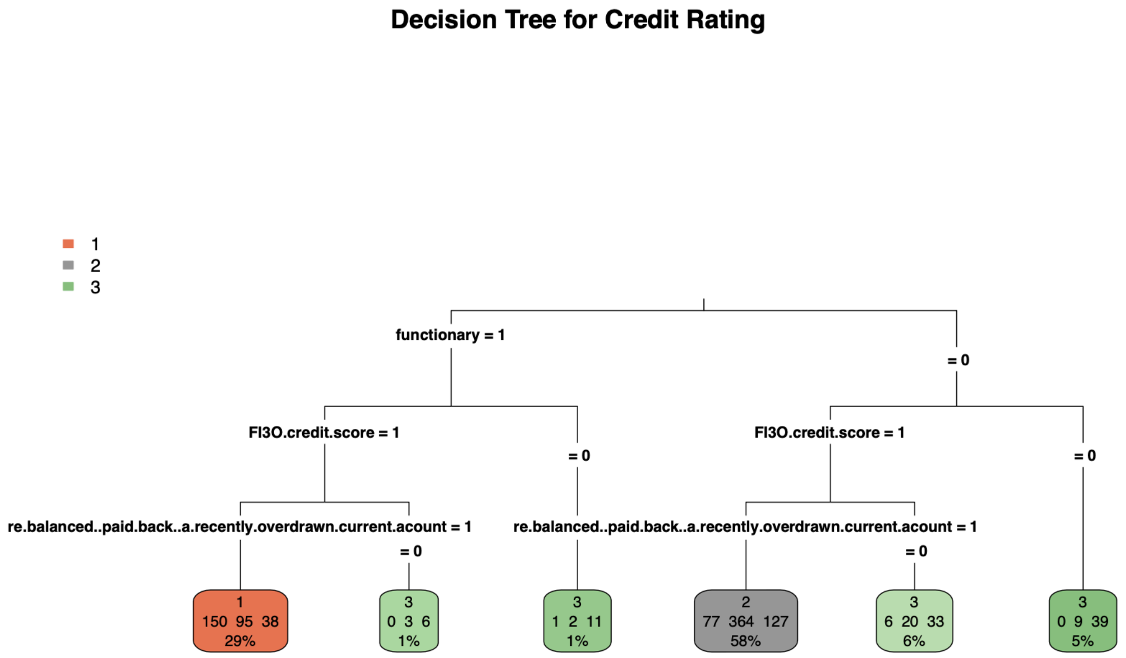
(a)Fit the decision tree model:



```r
# Q2.a
# install packages for decision tree
install.packages("tree")
install.packages("rpart.plot")
# loading resources
library(tree)
library(rpart)
library(randomForest)
library(rpart.plot)

# create a decision tree with rpart
tree_model = rpart(credit.rating~., data = train_set, method = "class")
# view the result of this decision tree
print(tree_model)
# plot the tree
rpart.plot(tree_model,
           main = "Decision Tree for Credit Rating",
           type = 3,
           extra = 101
)
```



```
> # view the result of this decision tree
> print(tree_model)
n= 981

node), split, n, loss, yval, (yprob)
      * denotes terminal node

 1) root 981 488 2 (0.23853211 0.50254842 0.25891947)
   2) functionary>=0.5 306 155 1 (0.49346405 0.32679739 0.17973856)
     4) FI3O.credit.score>=0.5 292 142 1 (0.51369863 0.33561644 0.15068493)
       8) re.balanced..paid.back..a.recently.overdrawn.current.acount>=0.5 283 133 1 (0.53003534 0.33568905 0.13427562) *
       9) re.balanced..paid.back..a.recently.overdrawn.current.acount< 0.5 9   3 3 (0.00000000 0.33333333 0.66666667) *
     5) FI3O.credit.score< 0.5 14   3 3 (0.07142857 0.14285714 0.78571429) *
   3) functionary< 0.5 675 282 2 (0.12296296 0.58222222 0.29481481)
     6) FI3O.credit.score>=0.5 627 243 2 (0.13237640 0.61244019 0.25518341)
      12) re.balanced..paid.back..a.recently.overdrawn.current.acount>=0.5 568 204 2 (0.13556338 0.64084507 0.22359155) *
      13) re.balanced..paid.back..a.recently.overdrawn.current.acount< 0.5 59  26 3 (0.10169492 0.33898305 0.55932203) *
     7) FI3O.credit.score< 0.5 48   9 3 (0.00000000 0.18750000 0.81250000) *
```


Decision Tree for Credit Rating
1
2
3
functionary = 1
= 0
FI3O.credit.score = 1
= 0
FI3O.credit.score = 1
= 0
re.balanced..paid.back..a.recently.overdrawn.current.acount = 1
= 0
re.balanced..paid.back..a.recently.overdrawn.current.acount = 1
= 0
1
150 95 38
29%
3
0 3 6
1%
3
1 2 11
1%
2
77 364 127
58%
3
6 20 33
6%
3
0 9 39
5%

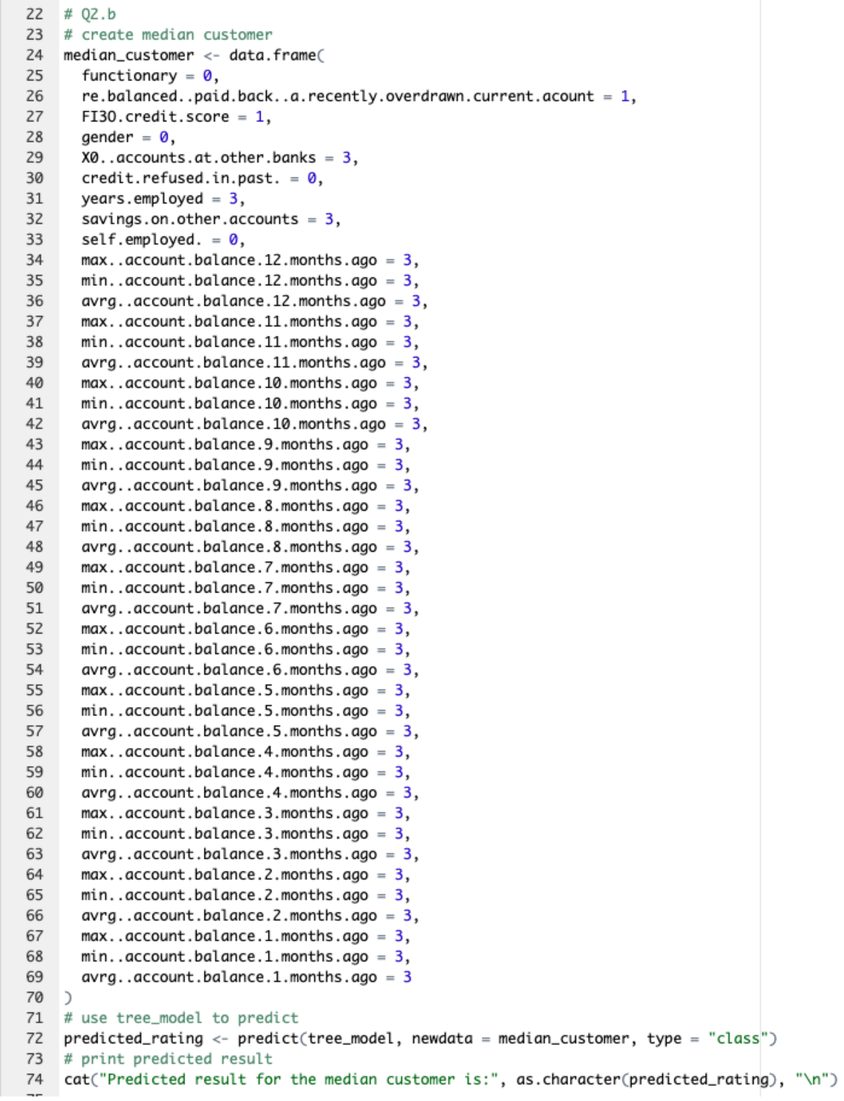
The root node contains 981 instances in the training set, among which 488 are misclassified. The majority class is **Class 2**, and the class distribution at the root node is 23.85% for Class 1, 50.25% for Class 2, and 25.89% for Class 3.

The first split occurs on the binary variable functionary, where:

- If **functionary = 1**, the left branch contains **306 instances**, the majority class is **Class 1** (49.35%). The next split is on FI30.credit.score = 1:
  - **If yes**, we get 283 instances, which are further split based on re.balanced..account = 1.
    - If yes, **150 instances** belong to Class 1, majority class =1.
    - If no, **6 instances** belong to Class 3, majority class = 3.
  - If FI30.credit.score = 0**,** the path leads to **14 instances**, majority class = 3.
- If **functionary = 0**, the right branch has **675 instances**, the majority class is Class 2 (58.22%). The next split is again on FI30.credit.score= 1.
  - **If yes**, we obtain **568 instances**, which are further split on **re.balanced..account**:
    - If = 1 -> majority class = 2.
    - If = 0 -> majority class = 3.
  - If FI30.credit.score= 0, the path leads to **48 instances**, and Class 3 is the majority.

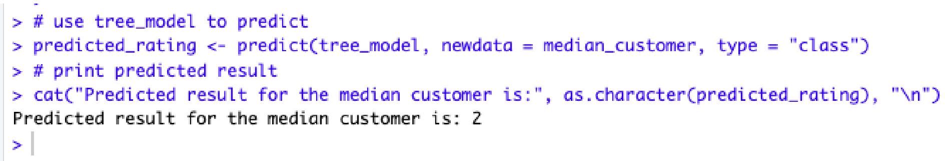
Asterisk (*) represent leaf nodes, where the decision path terminates.

(b) Create "median" customer and prediction:



```
# Q2.b
# create median customer
median_customer <- data.frame(
  functionary = 0,
  re.balanced..paid.back..a.recently.overdrawn.current.acount = 1,
  FI30.credit.score = 1,
  gender = 0,
  X0..accounts.at.other.banks = 3,
  credit.refused.in.past. = 0,
  years.employed = 3,
  savings.on.other.accounts = 3,
  self.employed. = 0,
  max..account.balance.12.months.ago = 3,
  min..account.balance.12.months.ago = 3,
  avrg..account.balance.12.months.ago = 3,
  max..account.balance.11.months.ago = 3,
  min..account.balance.11.months.ago = 3,
  avrg..account.balance.11.months.ago = 3,
  max..account.balance.10.months.ago = 3,
  min..account.balance.10.months.ago = 3,
  avrg..account.balance.10.months.ago = 3,
  max..account.balance.9.months.ago = 3,
  min..account.balance.9.months.ago = 3,
  avrg..account.balance.9.months.ago = 3,
  max..account.balance.8.months.ago = 3,
  min..account.balance.8.months.ago = 3,
  avrg..account.balance.8.months.ago = 3,
  max..account.balance.7.months.ago = 3,
  min..account.balance.7.months.ago = 3,
  avrg..account.balance.7.months.ago = 3,
  max..account.balance.6.months.ago = 3,
  min..account.balance.6.months.ago = 3,
  avrg..account.balance.6.months.ago = 3,
  max..account.balance.5.months.ago = 3,
  min..account.balance.5.months.ago = 3,
  avrg..account.balance.5.months.ago = 3,
  max..account.balance.4.months.ago = 3,
  min..account.balance.4.months.ago = 3,
  avrg..account.balance.4.months.ago = 3,
  max..account.balance.3.months.ago = 3,
  min..account.balance.3.months.ago = 3,
  avrg..account.balance.3.months.ago = 3,
  max..account.balance.2.months.ago = 3,
  min..account.balance.2.months.ago = 3,
  avrg..account.balance.2.months.ago = 3,
  max..account.balance.1.months.ago = 3,
  min..account.balance.1.months.ago = 3,
  avrg..account.balance.1.months.ago = 3
)
# use tree_model to predict
predicted_rating <- predict(tree_model, newdata = median_customer, type = "class")
# print predicted result
cat("Predicted result for the median customer is:", as.character(predicted_rating), "\n")
```

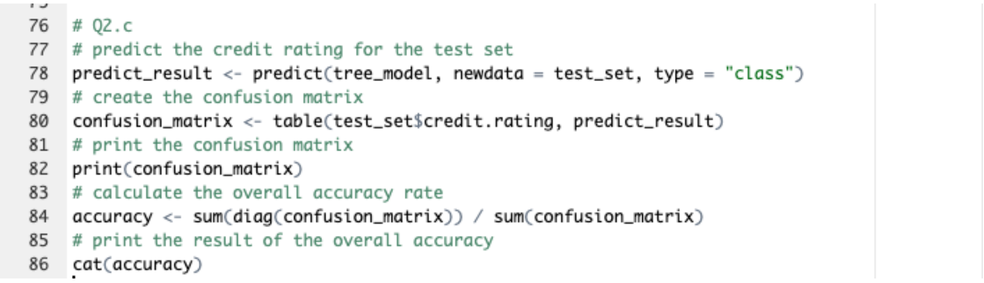
Verification results: The predicted credit rating of the median customer is **Class 2**.



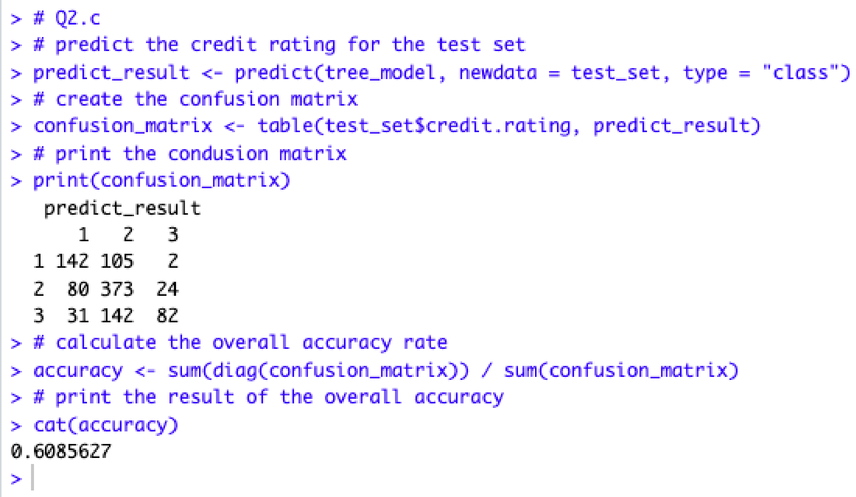
```
> # use tree_model to predict
> predicted_rating <- predict(tree_model, newdata = median_customer, type = "class")
> # print predicted result
> cat("Predicted result for the median customer is:", as.character(predicted_rating), "\n")
Predicted result for the median customer is: 2
> 
```

Based on the output of (a), the process is clearly presented:
functionary = 0 leads to the right child node (functionary < 0.5), FI3O.credit.score = 1 leads to the left child node (FI3O.credit.score>=0.5), re.balanced.paid.back...account = 1 leads to the left child node (>= 0.5). And a terminal node that predicts **Class 2** as the credit rating**.** The results of code verification are consistent with this process.

(c) Create confusion matrix and prediction code:



```
# Q2.c
# predict the credit rating for the test set
predict_result <- predict(tree_model, newdata = test_set, type = "class")
# create the confusion matrix
confusion_matrix <- table(test_set$credit.rating, predict_result)
# print the confusion matrix
print(confusion_matrix)
# calculate the overall accuracy rate
accuracy <- sum(diag(confusion_matrix)) / sum(confusion_matrix)
# print the result of the overall accuracy
cat(accuracy)
```



```
> # Q2.c
> # predict the credit rating for the test set
> predict_result <- predict(tree_model, newdata = test_set, type = "class")
> # create the confusion matrix
> confusion_matrix <- table(test_set$credit.rating, predict_result)
> # print the condusion matrix
> print(confusion_matrix)
   predict_result
      1   2   3
  1 142 105   2
  2  80 373  24
  3  31 142  82
> # calculate the overall accuracy rate
> accuracy <- sum(diag(confusion_matrix)) / sum(confusion_matrix)
> # print the result of the overall accuracy
> cat(accuracy)
0.6085627
> 
```

For the confusion matrix, the rows are the actual classification and the columns are the predicted classifications.

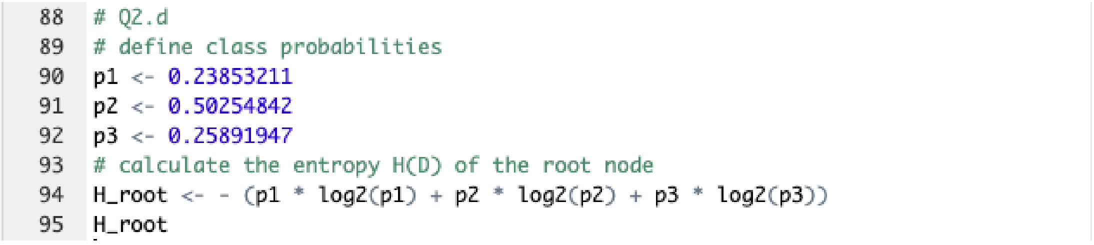
- Total number of correct predictions for each class = 142 + 373 + 82 = 597
- Total samples = 142 + 105 + 2 + 80 + 373 + 24 + 31 + 142 + 82 = 981
- Accuracy = 597 / 981 = 60.86%

(d)

1) Calculate the entropy of the root node

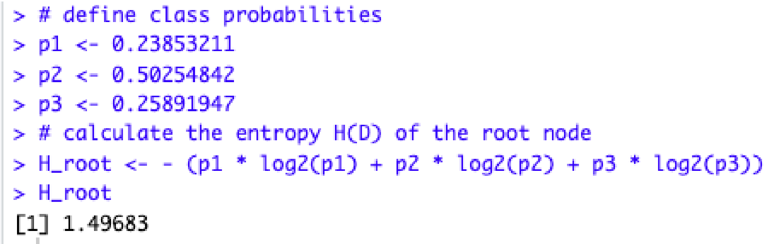
root 981 488 2 (0.23853211 0.50254842 0.25891947)

Step1: define class probabilities:



```r
# Q2.d
# define class probabilities
p1 <- 0.23853211
p2 <- 0.50254842
p3 <- 0.25891947
# calculate the entropy H(D) of the root node
H_root <- - (p1 * log2(p1) + p2 * log2(p2) + p3 * log2(p3))
H_root
```

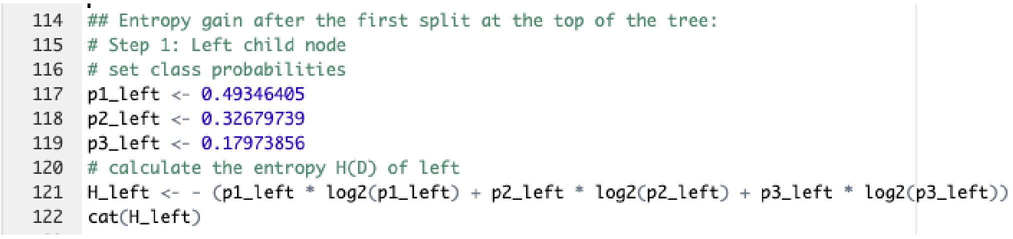
Step2: According to the entropy formula to calculate：
$H(D) = - (p1 \log_2 p1 + p2 \log_2 p2 + p3 \log_2 p3)$
$H(D) = - (0.23853211 * \log_2 0.23853211 + 0.50254842 * \log2\ 0.50254842 + 0.25891947 * \log2\ 0.25891947) \approx 1.49683$



```
> # define class probabilities
> p1 <- 0.23853211
> p2 <- 0.50254842
> p3 <- 0.25891947
> # calculate the entropy H(D) of the root node
> H_root <- - (p1 * log2(p1) + p2 * log2(p2) + p3 * log2(p3))
> H_root
[1] 1.49683
```

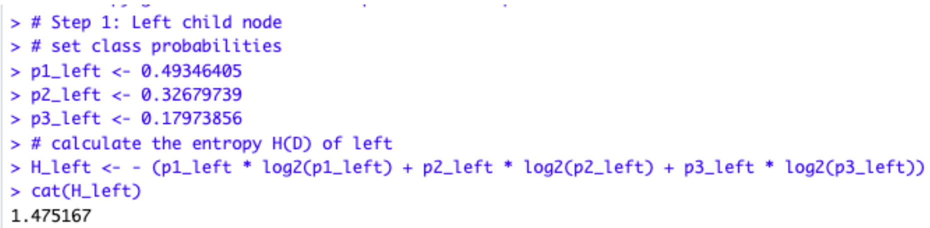
2) Entropy gain after the first split at the top of the tree:

Step 1: Left child node:
functionary>=0.5 306 155 1 (0.49346405 0.32679739 0.17973856)



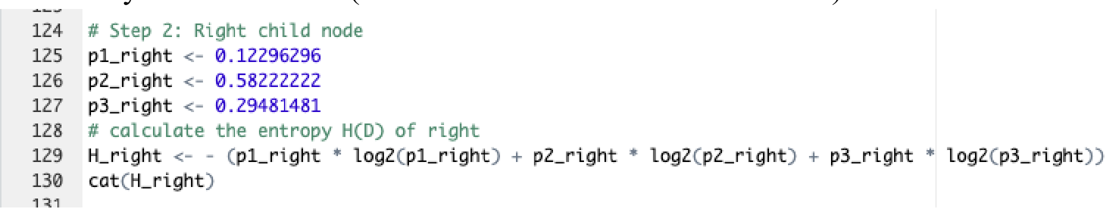
```r
## Entropy gain after the first split at the top of the tree:
# Step 1: Left child node
# set class probabilities
p1_left <- 0.49346405
p2_left <- 0.32679739
p3_left <- 0.17973856
# calculate the entropy H(D) of left
H_left <- - (p1_left * log2(p1_left) + p2_left * log2(p2_left) + p3_left * log2(p3_left))
cat(H_left)
```

The result of the left child node is 1.475167.



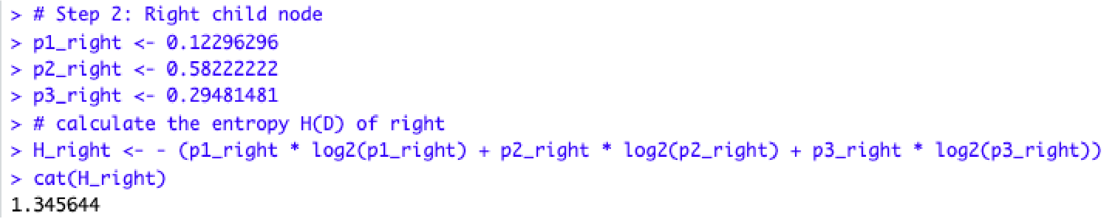
```
> # Step 1: Left child node
> # set class probabilities
> p1_left <- 0.49346405
> p2_left <- 0.32679739
> p3_left <- 0.17973856
> # calculate the entropy H(D) of left
> H_left <- - (p1_left * log2(p1_left) + p2_left * log2(p2_left) + p3_left * log2(p3_left))
> cat(H_left)
1.475167
```

Step 2: Right child node:
functionary< 0.5 675 282 2 (0.12296296 0.58222222 0.29481481)



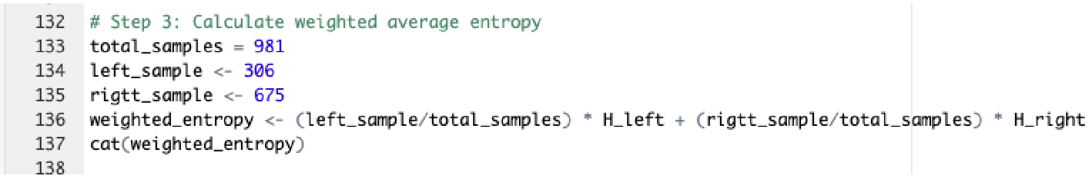
```r
# Step 2: Right child node
p1_right <- 0.12296296
p2_right <- 0.58222222
p3_right <- 0.29481481
# calculate the entropy H(D) of right
H_right <- - (p1_right * log2(p1_right) + p2_right * log2(p2_right) + p3_right * log2(p3_right))
cat(H_right)
```

The result of the right child node is 1.345644.



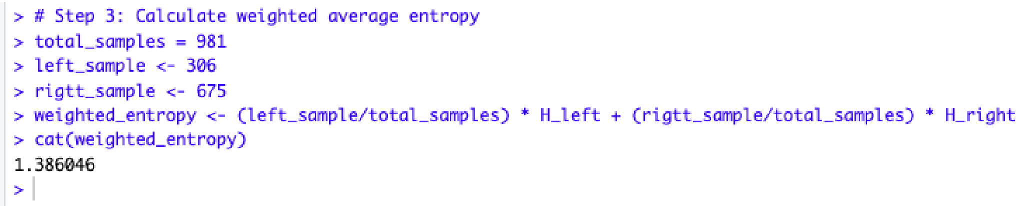
```
> # Step 2: Right child node
> p1_right <- 0.12296296
> p2_right <- 0.58222222
> p3_right <- 0.29481481
> # calculate the entropy H(D) of right
> H_right <- - (p1_right * log2(p1_right) + p2_right * log2(p2_right) + p3_right * log2(p3_right))
> cat(H_right)
1.345644
```

Step 3: Total first split total entropy:



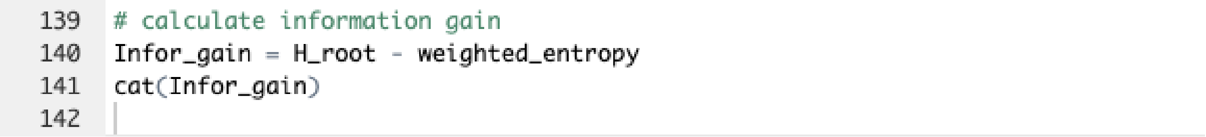
```
# Step 3: Calculate weighted average entropy
total_samples = 981
left_sample <- 306
rigtt_sample <- 675
weighted_entropy <- (left_sample/total_samples) * H_left + (rigtt_sample/total_samples) * H_right
cat(weighted_entropy)

```

The result of total first split total entropy is 1.386046.



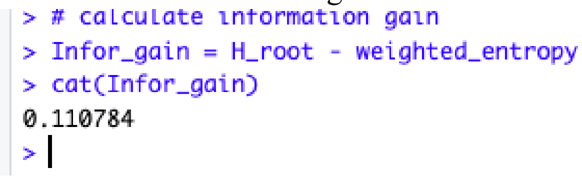
```
> # Step 3: Calculate weighted average entropy
> total_samples = 981
> left_sample <- 306
> rigtt_sample <- 675
> weighted_entropy <- (left_sample/total_samples) * H_left + (rigtt_sample/total_samples) * H_right
> cat(weighted_entropy)
1.386046
> 
```

3) Information gain = The entropy of the root node - Total first split total entropy = 1.49683 - 1.386046 = 0.110784



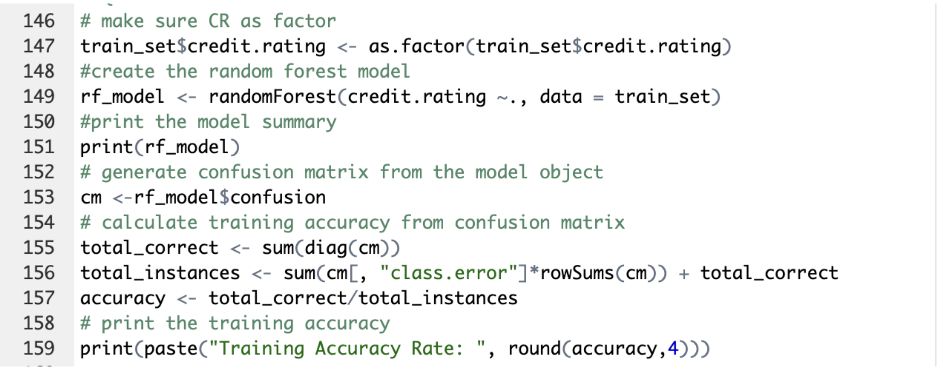
```
# calculate information gain
Infor_gain = H_root - weighted_entropy
cat(Infor_gain)

```

The result of information gain is **0.110784**.

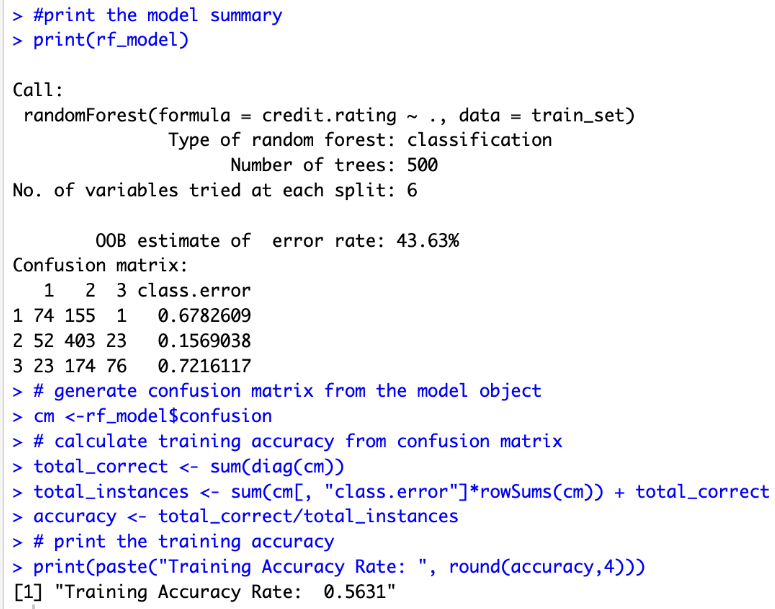


```
> # calculate information gain
> Infor_gain = H_root - weighted_entropy
> cat(Infor_gain)
0.110784
> 
```

(e) The code of my random forest model:



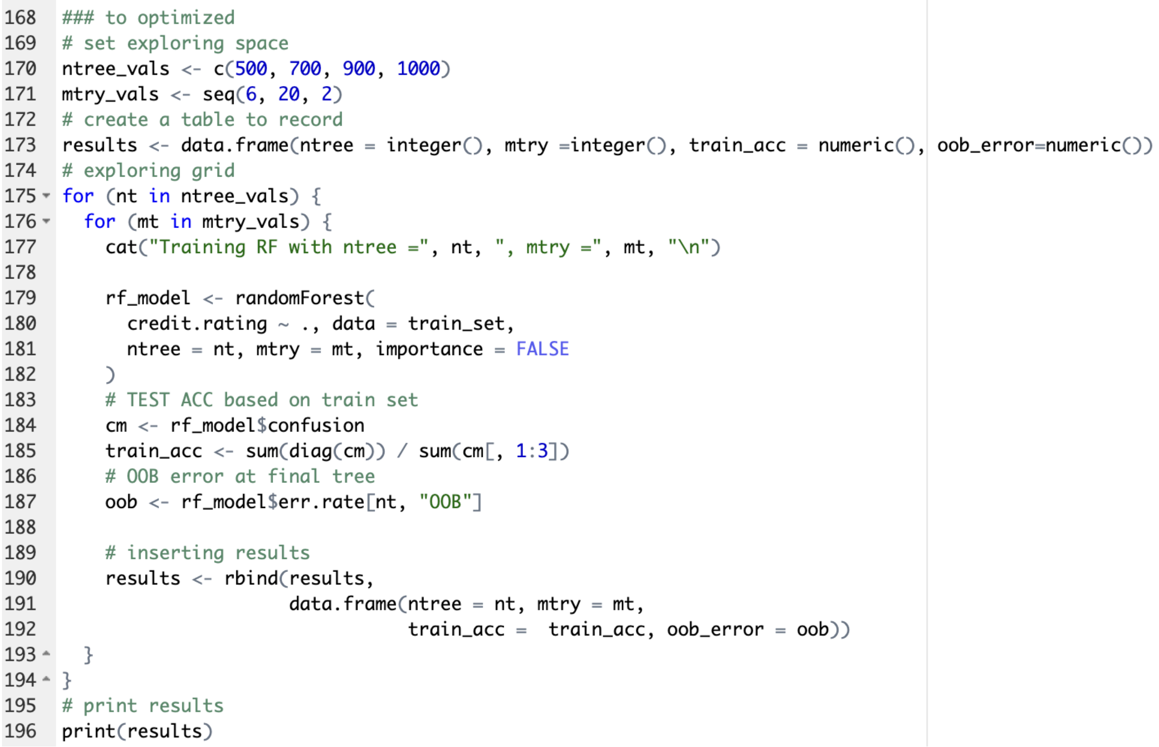
```
# make sure CR as factor
train_set$credit.rating <- as.factor(train_set$credit.rating)
#create the random forest model
rf_model <- randomForest(credit.rating ~., data = train_set)
#print the model summary
print(rf_model)
# generate confusion matrix from the model object
cm <-rf_model$confusion
# calculate training accuracy from confusion matrix
total_correct <- sum(diag(cm))
total_instances <- sum(cm[, "class.error"]*rowSums(cm)) + total_correct
accuracy <- total_correct/total_instances
# print the training accuracy
print(paste("Training Accuracy Rate: ", round(accuracy,4)))
```



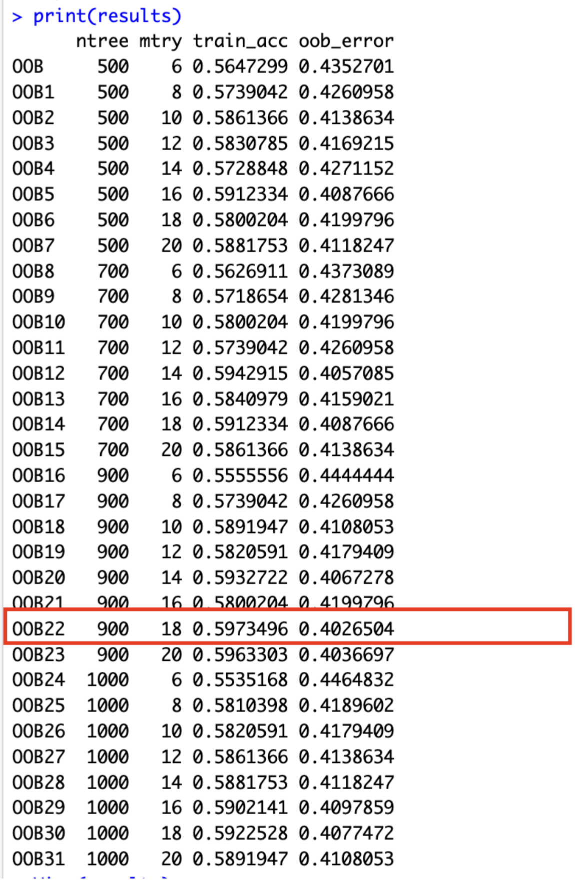
```
> #print the model summary
> print(rf_model)

Call:
 randomForest(formula = credit.rating ~ ., data = train_set)
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 6

        OOB estimate of  error rate: 43.63%
Confusion matrix:
   1   2  3 class.error
1 74 155  1   0.6782609
2 52 403 23   0.1569038
3 23 174 76   0.7216117
> # generate confusion matrix from the model object
> cm <-rf_model$confusion
> # calculate training accuracy from confusion matrix
> total_correct <- sum(diag(cm))
> total_instances <- sum(cm[, "class.error"]*rowSums(cm)) + total_correct
> accuracy <- total_correct/total_instances
> # print the training accuracy
> print(paste("Training Accuracy Rate: ", round(accuracy,4)))
[1] "Training Accuracy Rate:  0.5631"
```

The default value of Random Forest Model, ntree = 500, mtry = 6, and the OOB error rate in the training set is **43.63%**, the train set accuracy is **56.31%**.

To optimized code with automated tuning:



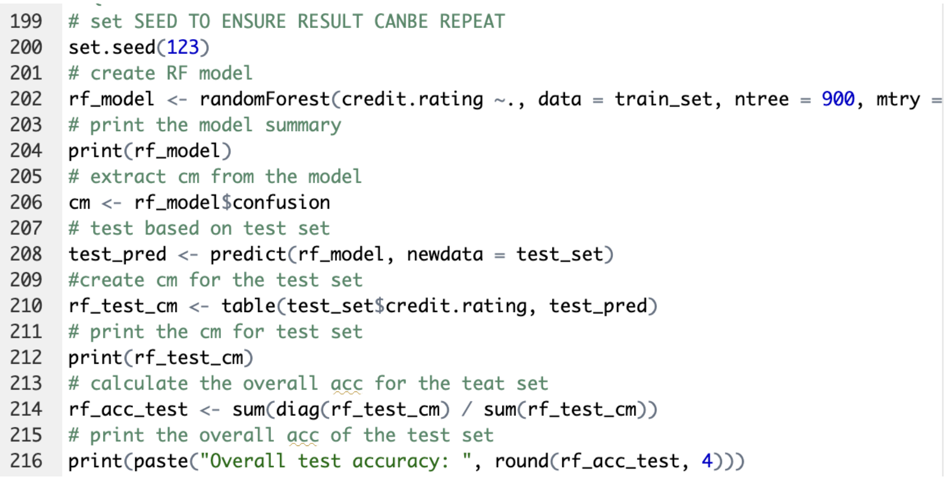
```
### to optimized
# set exploring space
ntree_vals <- c(500, 700, 900, 1000)
mtry_vals <- seq(6, 20, 2)
# create a table to record
results <- data.frame(ntree = integer(), mtry =integer(), train_acc = numeric(), oob_error=numeric())
# exploring grid
for (nt in ntree_vals) {
  for (mt in mtry_vals) {
    cat("Training RF with ntree =", nt, ", mtry =", mt, "\n")

    rf_model <- randomForest(
      credit.rating ~ ., data = train_set,
      ntree = nt, mtry = mt, importance = FALSE
    )
    # TEST ACC based on train set
    cm <- rf_model$confusion
    train_acc <- sum(diag(cm)) / sum(cm[, 1:3])
    # OOB error at final tree
    oob <- rf_model$err.rate[nt, "OOB"]

    # inserting results
    results <- rbind(results,
                     data.frame(ntree = nt, mtry = mt,
                                train_acc =  train_acc, oob_error = oob))
  }
}
# print results
print(results)
```



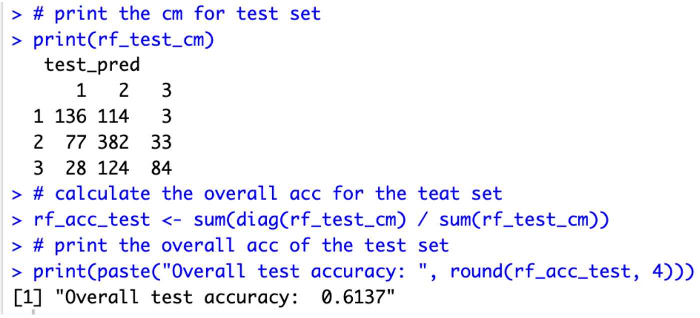
```
> print(results)
      ntree mtry train_acc oob_error
OOB     500    6 0.5647299 0.4352701
OOB1    500    8 0.5739042 0.4260958
OOB2    500   10 0.5861366 0.4138634
OOB3    500   12 0.5830785 0.4169215
OOB4    500   14 0.5728848 0.4271152
OOB5    500   16 0.5912334 0.4087666
OOB6    500   18 0.5800204 0.4199796
OOB7    500   20 0.5881753 0.4118247
OOB8    700    6 0.5626911 0.4373089
OOB9    700    8 0.5718654 0.4281346
OOB10   700   10 0.5800204 0.4199796
OOB11   700   12 0.5739042 0.4260958
OOB12   700   14 0.5942915 0.4057085
OOB13   700   16 0.5840979 0.4159021
OOB14   700   18 0.5912334 0.4087666
OOB15   700   20 0.5861366 0.4138634
OOB16   900    6 0.5555556 0.4444444
OOB17   900    8 0.5739042 0.4260958
OOB18   900   10 0.5891947 0.4108053
OOB19   900   12 0.5820591 0.4179409
OOB20   900   14 0.5932722 0.4067278
OOB21   900   16 0.5800204 0.4199796
OOB22   900   18 0.5973496 0.4026504
OOB23   900   20 0.5963303 0.4036697
OOB24  1000    6 0.5535168 0.4464832
OOB25  1000    8 0.5810398 0.4189602
OOB26  1000   10 0.5820591 0.4179409
OOB27  1000   12 0.5861366 0.4138634
OOB28  1000   14 0.5881753 0.4118247
OOB29  1000   16 0.5902141 0.4097859
OOB30  1000   18 0.5922528 0.4077472
OOB31  1000   20 0.5891947 0.4108053
```

The best parameter combination is **ntree = 900, mtry = 18**, with the highest accuracy of **59.73%** based on train set, and the lowest OBB error rate of **40.26%**.

(f) Predicting the credit rating using the random forest model on the test set



```r
# set SEED TO ENSURE RESULT CANBE REPEAT
set.seed(123)
# create RF model
rf_model <- randomForest(credit.rating ~., data = train_set, ntree = 900, mtry = 18)
# print the model summary
print(rf_model)
# extract cm from the model
cm <- rf_model$confusion
# test based on test set
test_pred <- predict(rf_model, newdata = test_set)
#create cm for the test set
rf_test_cm <- table(test_set$credit.rating, test_pred)
# print the cm for test set
print(rf_test_cm)
# calculate the overall acc for the teat set
rf_acc_test <- sum(diag(rf_test_cm) / sum(rf_test_cm))
# print the overall acc of the test set
print(paste("Overall test accuracy: ", round(rf_acc_test, 4)))
```



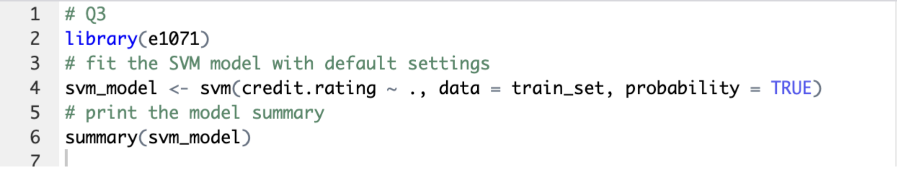
```
> # print the cm for test set
> print(rf_test_cm)
   test_pred
      1   2   3
  1 136 114   3
  2  77 382  33
  3  28 124  84
> # calculate the overall acc for the teat set
> rf_acc_test <- sum(diag(rf_test_cm) / sum(rf_test_cm))
> # print the overall acc of the test set
> print(paste("Overall test accuracy: ", round(rf_acc_test, 4)))
[1] "Overall test accuracy:  0.6137"
```

For the parameters ntree = 900, mtry = 18, the confusion matrix for predicting the credit rating from the random forest on the test set as follows, the overall accuracy is **61.37%**. Compared to the decision tree model used in (c), it is slightly higher than **60.86%** of the decision tree. This suggests that the random forest model had a slight edge in overall classification performance.

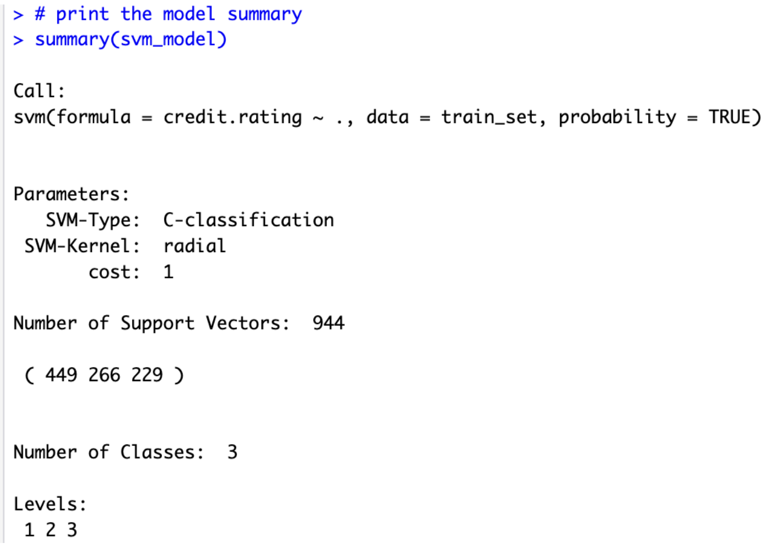
- For Class 1, the decision tree correctly classified 142 instances, outperforming the random forest's 136.
- For Class 2, the random forest model performed better, correctly classifying 382 instances, compared to 373 by the decision tree.
- For Class 3, the random forest also showed improved performance, predicting 84 instances correctly versus 82 by the decision tree.

3. SVM Hyperparameter Tuning and Modeling

Fit a support vector machine with default settings:



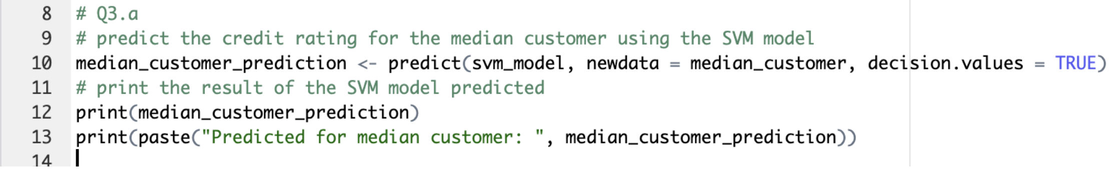
```
# Q3
library(e1071)
# fit the SVM model with default settings
svm_model <- svm(credit.rating ~ ., data = train_set, probability = TRUE)
# print the model summary
summary(svm_model)
```



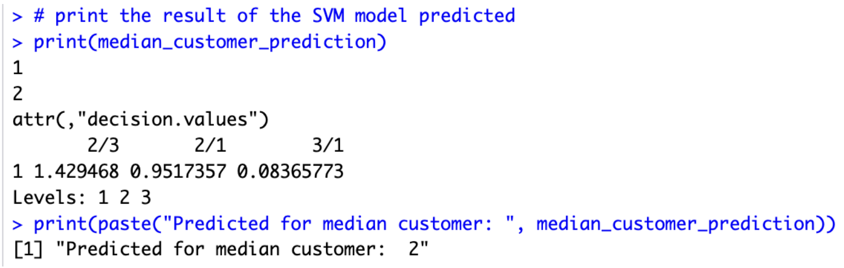
```
> # print the model summary
> summary(svm_model)

Call:
svm(formula = credit.rating ~ ., data = train_set, probability = TRUE)


Parameters:
   SVM-Type:  C-classification
 SVM-Kernel:  radial
       cost:  1

Number of Support Vectors:  944

 ( 449 266 229 )


Number of Classes:  3

Levels:
 1 2 3
```

The SVM model was fitted using an RBF (Radial Basis Function) kernel with default parameters. The penalty parameter was set to cost (c = 1), and a total of 944 support vectors were identified: 449 in Class 1, 266 in Class 2, and 229 in Class 3.

(a) Predict the credit rating of the median customer



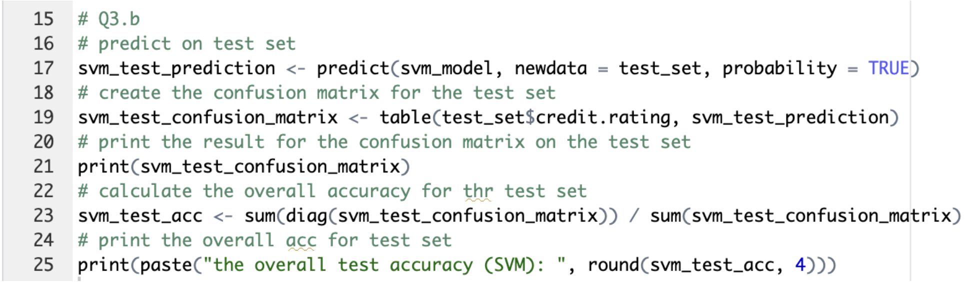
```
# Q3.a
# predict the credit rating for the median customer using the SVM model
median_customer_prediction <- predict(svm_model, newdata = median_customer, decision.values = TRUE)
# print the result of the SVM model predicted
print(median_customer_prediction)
print(paste("Predicted for median customer: ", median_customer_prediction))
```



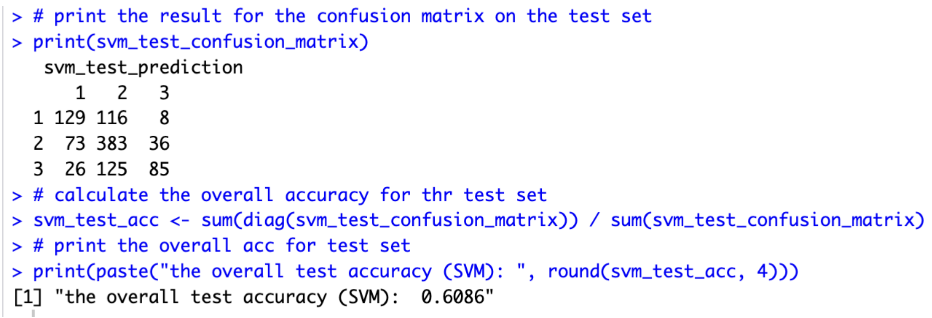
```
> # print the result of the SVM model predicted
> print(median_customer_prediction)
1
2
attr(,"decision.values")
       2/3       2/1        3/1
1 1.429468 0.9517357 0.08365773
Levels: 1 2 3
> print(paste("Predicted for median customer: ", median_customer_prediction))
[1] "Predicted for median customer:  2"
```

The predicted credit rating for the median customer is **Class 2**. The decision.values indicate a stronger preference for Class 2 compared to Class 1 and Class 3, as reflected in the higher margins: **2/3 = 1.43**, **2/1 = 0.95**.

(b)produce the confusion matrix for predicting the credit rating on test set



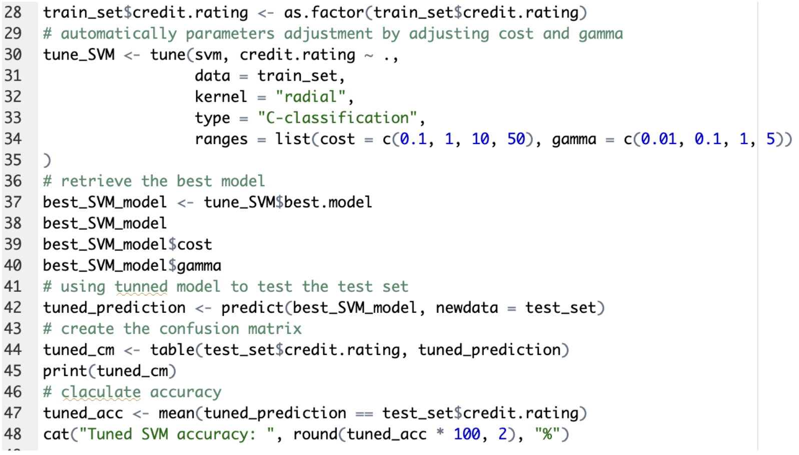
```
# Q3.b
# predict on test set
svm_test_prediction <- predict(svm_model, newdata = test_set, probability = TRUE)
# create the confusion matrix for the test set
svm_test_confusion_matrix <- table(test_set$credit.rating, svm_test_prediction)
# print the result for the confusion matrix on the test set
print(svm_test_confusion_matrix)
# calculate the overall accuracy for thr test set
svm_test_acc <- sum(diag(svm_test_confusion_matrix)) / sum(svm_test_confusion_matrix)
# print the overall acc for test set
print(paste("the overall test accuracy (SVM): ", round(svm_test_acc, 4)))
```



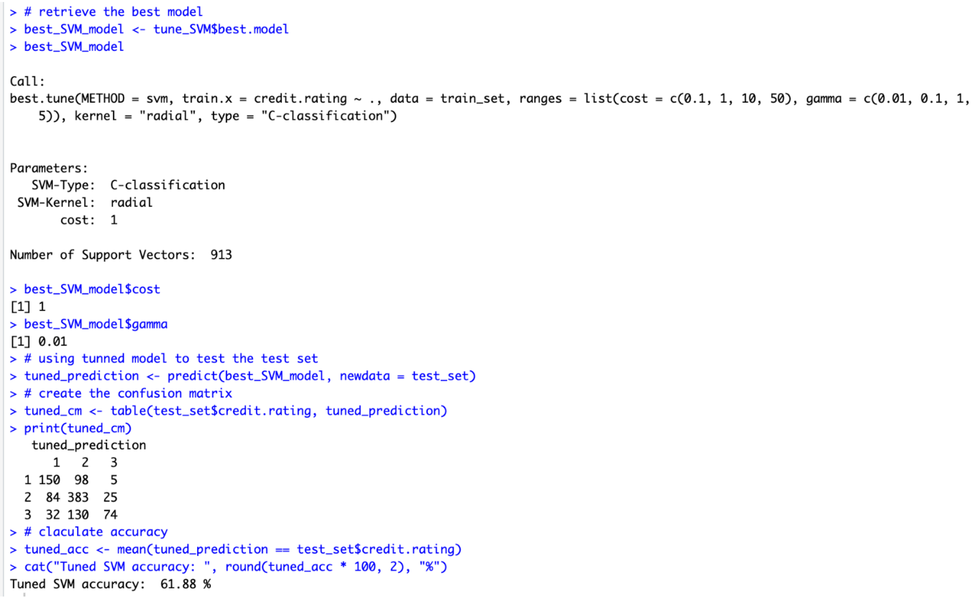
```
> # print the result for the confusion matrix on the test set
> print(svm_test_confusion_matrix)
   svm_test_prediction
      1   2   3
  1 129 116   8
  2  73 383  36
  3  26 125  85
> # calculate the overall accuracy for thr test set
> svm_test_acc <- sum(diag(svm_test_confusion_matrix)) / sum(svm_test_confusion_matrix)
> # print the overall acc for test set
> print(paste("the overall test accuracy (SVM): ", round(svm_test_acc, 4)))
[1] "the overall test accuracy (SVM):  0.6086"
```

The overall test accuracy of the SVM model is **60.86%**, based on the confusion matrix with 129, 383, and 85 correct predictions for Classes 1, 2, and 3 respectively.
Calculation: (129 + 383 + 85) / 981 = 60.86%

(c) Automatically tune the SVM to improve prediction



```
train_set$credit.rating <- as.factor(train_set$credit.rating)
# automatically parameters adjustment by adjusting cost and gamma
tune_SVM <- tune(svm, credit.rating ~ .,
                 data = train_set,
                 kernel = "radial",
                 type = "C-classification",
                 ranges = list(cost = c(0.1, 1, 10, 50), gamma = c(0.01, 0.1, 1, 5))
)
# retrieve the best model
best_SVM_model <- tune_SVM$best.model
best_SVM_model
best_SVM_model$cost
best_SVM_model$gamma
# using tunned model to test the test set
tuned_prediction <- predict(best_SVM_model, newdata = test_set)
# create the confusion matrix
tuned_cm <- table(test_set$credit.rating, tuned_prediction)
print(tuned_cm)
# claculate accuracy
tuned_acc <- mean(tuned_prediction == test_set$credit.rating)
cat("Tuned SVM accuracy: ", round(tuned_acc * 100, 2), "%")
```



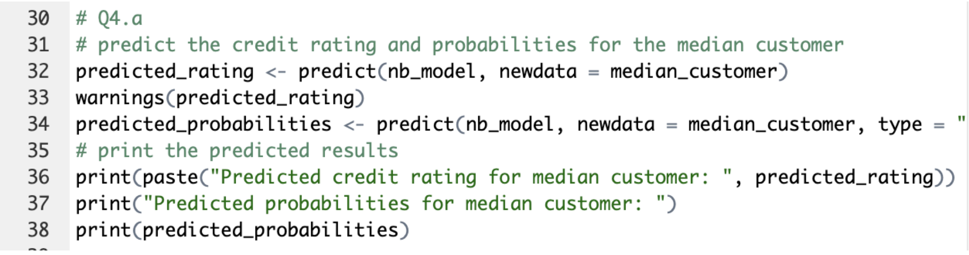
```
> # retrieve the best model
> best_SVM_model <- tune_SVM$best.model
> best_SVM_model

Call:
best.tune(METHOD = svm, train.x = credit.rating ~ ., data = train_set, ranges = list(cost = c(0.1, 1, 10, 50), gamma = c(0.01, 0.1, 1, 
    5)), kernel = "radial", type = "C-classification")


Parameters:
   SVM-Type:  C-classification 
 SVM-Kernel:  radial 
       cost:  1 

Number of Support Vectors:  913

> best_SVM_model$cost
[1] 1
> best_SVM_model$gamma
[1] 0.01
> # using tunned model to test the test set
> tuned_prediction <- predict(best_SVM_model, newdata = test_set)
> # create the confusion matrix
> tuned_cm <- table(test_set$credit.rating, tuned_prediction)
> print(tuned_cm)
   tuned_prediction
      1   2   3
  1 150  98   5
  2  84 383  25
  3  32 130  74
> # claculate accuracy
> tuned_acc <- mean(tuned_prediction == test_set$credit.rating)
> cat("Tuned SVM accuracy: ", round(tuned_acc * 100, 2), "%")
Tuned SVM accuracy:  61.88 %
```

Overall test accuracy of the tuned model is: **61.88%**, which improves upon the default model's **60.86%** accuracy reported in Q3(b). To improve the performance of the default SVM model, I performed parameter tuning by adjusting the cost and gamma values, and found the **best parameter combination** was: **cost = 1**, **gamma = 0.01**.
The tuning process led to a slight but meaningful improvement in classification performance. In particular:

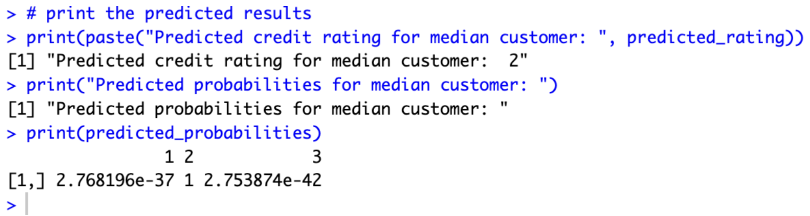
- Class 1 prediction improved (150 vs. 129 correct in default model), indicating significant improvement.
- Class 2 accuracy remained strong (383 vs. 383), indicating reaching stability.
- Class 3 prediction slightly decreased (74 vs. 85), indicating potential trade-offs.

4. Naive Bayes Classification Analysis

(a)Predict the credit rating of the median customer on the Naive Bayes model



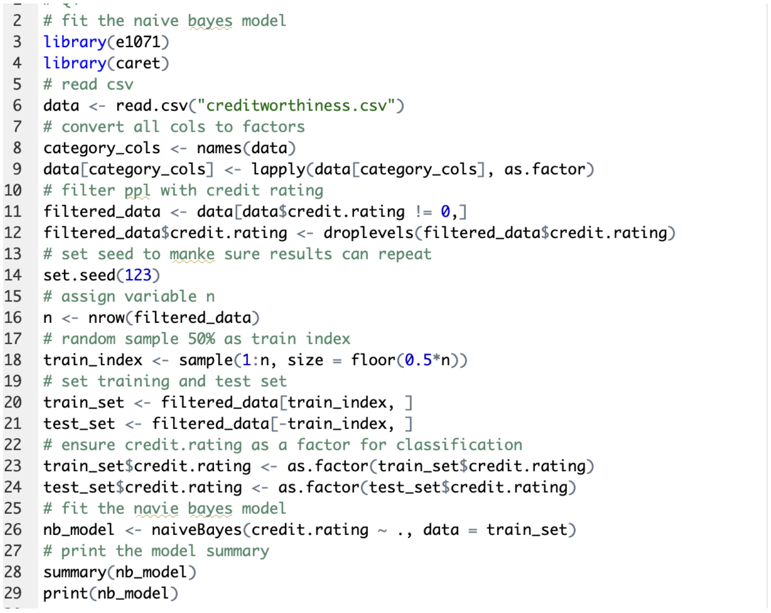
```
# Q4.a
# predict the credit rating and probabilities for the median customer
predicted_rating <- predict(nb_model, newdata = median_customer)
warnings(predicted_rating)
predicted_probabilities <- predict(nb_model, newdata = median_customer, type = "raw")
# print the predicted results
print(paste("Predicted credit rating for median customer: ", predicted_rating))
print("Predicted probabilities for median customer: ")
print(predicted_probabilities)
```



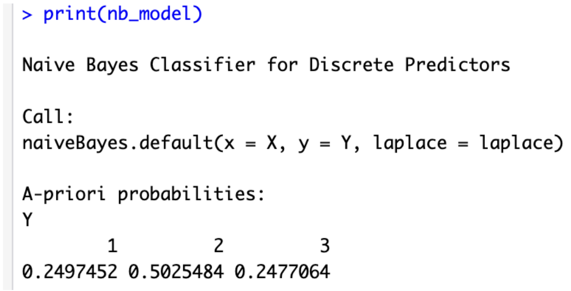
```
> # print the predicted results
> print(paste("Predicted credit rating for median customer: ", predicted_rating))
[1] "Predicted credit rating for median customer:  2"
> print("Predicted probabilities for median customer: ")
[1] "Predicted probabilities for median customer: "
> print(predicted_probabilities)
                1 2            3
[1,] 2.768196e-37 1 2.753874e-42
> 
```

The Naive Bayes model confirms that the median customer belongs to **Class 2** with extremely high confidence (1), while probabilities for Class 1 (= 2.768196e-37) and Class 3 (= 2.753874e-42) are effectively 0.

(b)Fit the naive bayes model



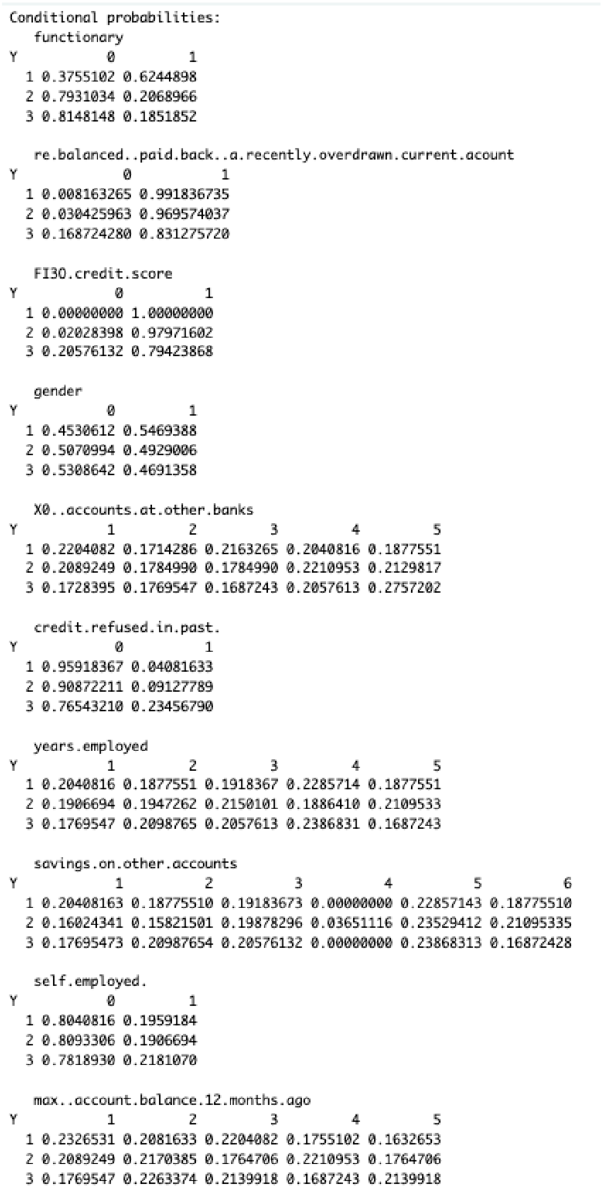
```
# fit the naive bayes model
library(e1071)
library(caret)
# read csv
data <- read.csv("creditworthiness.csv")
# convert all cols to factors
category_cols <- names(data)
data[category_cols] <- lapply(data[category_cols], as.factor)
# filter ppl with credit rating
filtered_data <- data[data$credit.rating != 0,]
filtered_data$credit.rating <- droplevels(filtered_data$credit.rating)
# set seed to manke sure results can repeat
set.seed(123)
# assign variable n
n <- nrow(filtered_data)
# random sample 50% as train index
train_index <- sample(1:n, size = floor(0.5*n))
# set training and test set
train_set <- filtered_data[train_index, ]
test_set <- filtered_data[-train_index, ]
# ensure credit.rating as a factor for classification
train_set$credit.rating <- as.factor(train_set$credit.rating)
test_set$credit.rating <- as.factor(test_set$credit.rating)
# fit the navie bayes model
nb_model <- naiveBayes(credit.rating ~ ., data = train_set)
# print the model summary
summary(nb_model)
print(nb_model)
```



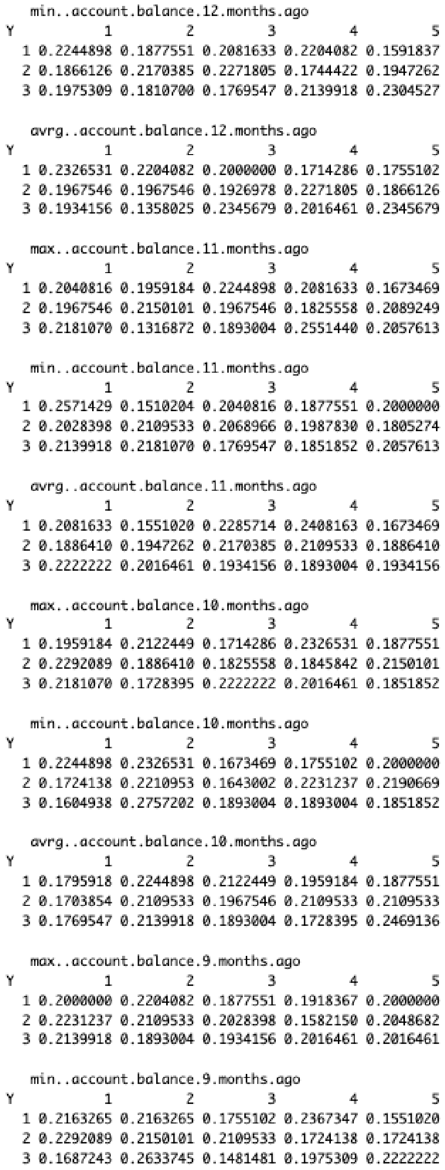
```
> print(nb_model)

Naive Bayes Classifier for Discrete Predictors

Call:
naiveBayes.default(x = X, y = Y, laplace = laplace)

A-priori probabilities:
Y
        1         2         3 
0.2497452 0.5025484 0.2477064 
```

Step 1: A-priori probabilities showed that of the probabilities of each class in the training data :

- P (Y = A) = P(Y = 1) = 0.2497452
- P (Y = B) = P(Y = 2) = 0.5025484
- P (Y = C) = P(Y = 3) = 0.2477064



```
Conditional probabilities:
   functionary
Y           0         1
  1 0.3755102 0.6244898
  2 0.7931034 0.2068966
  3 0.8148148 0.1851852

   re.balanced..paid.back..a.recently.overdrawn.current.acount
Y             0           1
  1 0.008163265 0.991836735
  2 0.030425963 0.969574037
  3 0.168724280 0.831275720

   FI3O.credit.score
Y            0          1
  1 0.00000000 1.00000000
  2 0.02028398 0.97971602
  3 0.20576132 0.79423868

   gender
Y           0         1
  1 0.4530612 0.5469388
  2 0.5070994 0.4929006
  3 0.5308642 0.4691358

   X0..accounts.at.other.banks
Y           1         2         3         4         5
  1 0.2204082 0.1714286 0.2163265 0.2040816 0.1877551
  2 0.2089249 0.1784990 0.1784990 0.2210953 0.2129817
  3 0.1728395 0.1769547 0.1687243 0.2057613 0.2757202

   credit.refused.in.past.
Y            0          1
  1 0.95918367 0.04081633
  2 0.90872211 0.09127789
  3 0.76543210 0.23456790

   years.employed
Y           1         2         3         4         5
  1 0.2040816 0.1877551 0.1918367 0.2285714 0.1877551
  2 0.1906694 0.1947262 0.2150101 0.1886410 0.2109533
  3 0.1769547 0.2098765 0.2057613 0.2386831 0.1687243

   savings.on.other.accounts
Y            1          2          3          4          5          6
  1 0.20408163 0.18775510 0.19183673 0.00000000 0.22857143 0.18775510
  2 0.16024341 0.15821501 0.19878296 0.03651116 0.23529412 0.21095335
  3 0.17695473 0.20987654 0.20576132 0.00000000 0.23868313 0.16872428

   self.employed.
Y           0         1
  1 0.8040816 0.1959184
  2 0.8093306 0.1906694
  3 0.7818930 0.2181070

   max..account.balance.12.months.ago
Y           1         2         3         4         5
  1 0.2326531 0.2081633 0.2204082 0.1755102 0.1632653
  2 0.2089249 0.2170385 0.1764706 0.2210953 0.1764706
  3 0.1769547 0.2263374 0.2139918 0.1687243 0.2139918
```



```
   min..account.balance.12.months.ago
Y           1         2         3         4         5
  1 0.2244898 0.1877551 0.2081633 0.2204082 0.1591837
  2 0.1866126 0.2170385 0.2271805 0.1744422 0.1947262
  3 0.1975309 0.1810700 0.1769547 0.2139918 0.2304527

   avrg..account.balance.12.months.ago
Y           1         2         3         4         5
  1 0.2326531 0.2204082 0.2000000 0.1714286 0.1755102
  2 0.1967546 0.1967546 0.1926978 0.2271805 0.1866126
  3 0.1934156 0.1358025 0.2345679 0.2016461 0.2345679

   max..account.balance.11.months.ago
Y           1         2         3         4         5
  1 0.2040816 0.1959184 0.2244898 0.2081633 0.1673469
  2 0.1967546 0.2150101 0.1967546 0.1825558 0.2089249
  3 0.2181070 0.1316872 0.1893004 0.2551440 0.2057613

   min..account.balance.11.months.ago
Y           1         2         3         4         5
  1 0.2571429 0.1510204 0.2040816 0.1877551 0.2000000
  2 0.2028398 0.2109533 0.2068966 0.1987830 0.1805274
  3 0.2139918 0.2181070 0.1769547 0.1851852 0.2057613

   avrg..account.balance.11.months.ago
Y           1         2         3         4         5
  1 0.2081633 0.1551020 0.2285714 0.2408163 0.1673469
  2 0.1886410 0.1947262 0.2170385 0.2109533 0.1886410
  3 0.2222222 0.2016461 0.1934156 0.1893004 0.1934156

   max..account.balance.10.months.ago
Y           1         2         3         4         5
  1 0.1959184 0.2122449 0.1714286 0.2326531 0.1877551
  2 0.2292089 0.1886410 0.1825558 0.1845842 0.2150101
  3 0.2181070 0.1728395 0.2222222 0.2016461 0.1851852

   min..account.balance.10.months.ago
Y           1         2         3         4         5
  1 0.2244898 0.2326531 0.1673469 0.1755102 0.2000000
  2 0.1724138 0.2210953 0.1643002 0.2231237 0.2190669
  3 0.1604938 0.2757202 0.1893004 0.1893004 0.1851852

   avrg..account.balance.10.months.ago
Y           1         2         3         4         5
  1 0.1795918 0.2244898 0.2122449 0.1959184 0.1877551
  2 0.1703854 0.2109533 0.1967546 0.2109533 0.2109533
  3 0.1769547 0.2139918 0.1893004 0.1728395 0.2469136

   max..account.balance.9.months.ago
Y           1         2         3         4         5
  1 0.2000000 0.2204082 0.1877551 0.1918367 0.2000000
  2 0.2231237 0.2109533 0.2028398 0.1582150 0.2048682
  3 0.2139918 0.1893004 0.1934156 0.2016461 0.2016461

   min..account.balance.9.months.ago
Y           1         2         3         4         5
  1 0.2163265 0.2163265 0.1755102 0.2367347 0.1551020
  2 0.2292089 0.2150101 0.2109533 0.1724138 0.1724138
  3 0.1687243 0.2633745 0.1481481 0.1975309 0.2222222
```

Step 2: Conditional probabilities of the Top 20 attributes from R output. For example, the variable functionary as x = 0, so we look at:

- P(x = 0 | Y = 1) = 0.3755102
- P(x = 0 | Y = 2) = 0.7931034
- P(x = 0 | Y = 3) = 0.8148148

Step 3: Apply the Naive Bayes formula using the priori and conditional probabilities for the 20 attributes based on data.frame of the median customer.

Let X = (x_1 = 0, x_2 = 1, x_3 = 1,...,x_{20} = 3) be the features of the median customer data frame, the corresponding values are:

- x_1 = 0 (functionary = 0)
- x_2 = 1 (rebalance..paid.back = 1)
- x_3 = 1 (FI3O.credit.score = 1)

- …
- x_{20} = 3 (min.balance.9.months.ago = 3)

P_1 : $P(Y=1) * P(x_1 \mid Y=1)* P(x_2 \mid Y=1)* P(x_3 \mid Y=1)* P(x_4 \mid Y=1)* P(x_5 \mid Y=1)* P(x_6 \mid Y=1)* P(x_7 \mid Y=1)* P(x_8 \mid Y=1)* P(x_9 \mid Y=1)* P(x_{10} \mid Y=1)* P(x_{11} \mid Y=1)* P(x_{12} \mid Y=1)* P(x_{13} \mid Y=1)* P(x_{14} \mid Y=1)* P(x_{15} \mid Y=1)* P(x_{16} \mid Y=1)* P(x_{17} \mid Y=1)* P(x_{18} \mid Y=1)* P(x_{19} \mid Y=1)* P(x_{20} \mid Y=1)$

P_2 : $P(Y=2) * P(x_1 \mid Y=2)* P(x_2 \mid Y=2)* P(x_3 \mid Y=2)* P(x_4 \mid Y=2)* P(x_5 \mid Y=2)* P(x_6 \mid Y=2)* P(x_7 \mid Y=2)* P(x_8 \mid Y=2)* P(x_9 \mid Y=2)* P(x_{10} \mid Y=2)* P(x_{11} \mid Y=2)* P(x_{12} \mid Y=2)* P(x_{13} \mid Y=2)* P(x_{14} \mid Y=2)* P(x_{15} \mid Y=2)* P(x_{16} \mid Y=2)* P(x_{17} \mid Y=2)* P(x_{18} \mid Y=2)* P(x_{19} \mid Y=2)* P(x_{20} \mid Y=2)$

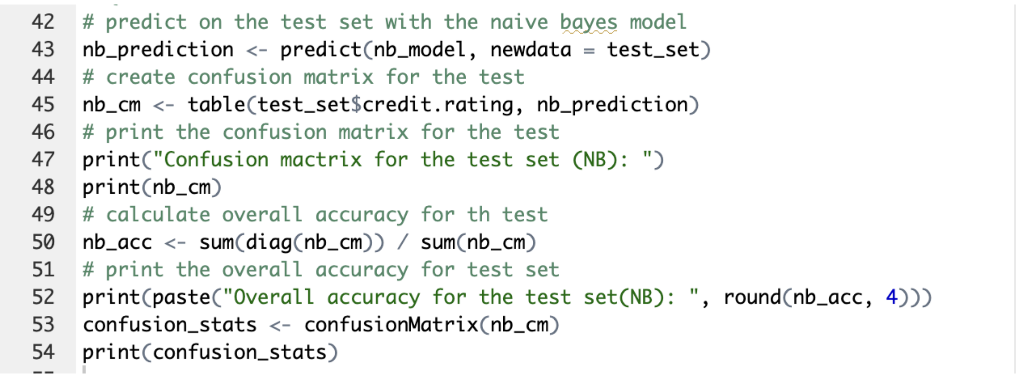
P_3 : $P(Y=3) * P(x_1 \mid Y=3)* P(x_2 \mid Y=3)* P(x_3 \mid Y=3)* P(x_4 \mid Y=3)* P(x_5 \mid Y=3)* P(x_6 \mid Y=3)* P(x_7 \mid Y=3)* P(x_8 \mid Y=3)* P(x_9 \mid Y=3)* P(x_{10} \mid Y=3)* P(x_{11} \mid Y=3)* P(x_{12} \mid Y=3)* P(x_{13} \mid Y=3)* P(x_{14} \mid Y=3)* P(x_{15} \mid Y=3)* P(x_{16} \mid Y=3)* P(x_{17} \mid Y=3)* P(x_{18} \mid Y=3)* P(x_{19} \mid Y=3)* P(x_{20} \mid Y=3)$

Then, we normalize to obtain the posterior probabilities:

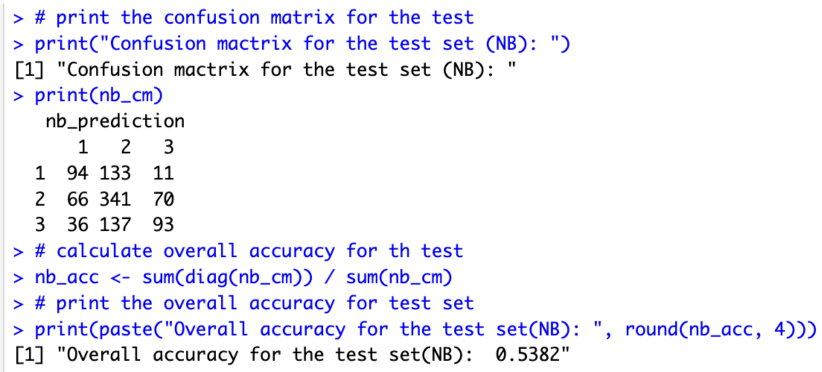
$P(Y=k \mid X) = P_k / (P_1 + P_2 + P_3)$, with k = 1, 2, 3

And assign the class with the highest posterior as the predicted label.

(c)Predicting the credit rating using naive bayes on the test set



```
# predict on the test set with the naive bayes model
nb_prediction <- predict(nb_model, newdata = test_set)
# create confusion matrix for the test
nb_cm <- table(test_set$credit.rating, nb_prediction)
# print the confusion matrix for the test
print("Confusion mactrix for the test set (NB): ")
print(nb_cm)
# calculate overall accuracy for th test
nb_acc <- sum(diag(nb_cm)) / sum(nb_cm)
# print the overall accuracy for test set
print(paste("Overall accuracy for the test set(NB): ", round(nb_acc, 4)))
confusion_stats <- confusionMatrix(nb_cm)
print(confusion_stats)
```



```
> # print the confusion matrix for the test
> print("Confusion mactrix for the test set (NB): ")
[1] "Confusion mactrix for the test set (NB): "
> print(nb_cm)
   nb_prediction
     1   2   3
  1  94 133  11
  2  66 341  70
  3  36 137  93
> # calculate overall accuracy for th test
> nb_acc <- sum(diag(nb_cm)) / sum(nb_cm)
> # print the overall accuracy for test set
> print(paste("Overall accuracy for the test set(NB): ", round(nb_acc, 4)))
[1] "Overall accuracy for the test set(NB):  0.5382"
```

The overall accuracy rate using the Naive Bayes model on the test set is **53.82%,** calculated as (94 + 341 + 93) / (94+133+11+66+341+70+36+137+93) = 528 / 981 = 0.5382263.

- For Class 1 (total: 238 samples), 94 were correctly classified, while 133 were misclassified as Class 2 and 11 as Class 3.
- For Class 2 (total: 477 samples), 341 were correctly classified, with 66 misclassified as Class 1 and 70 as Class 3.
- For Class 3 (total: 266 samples), 93 were correctly classified, while 36 were misclassified as Class 1 and 137 as Class 2.

5. Model Benchmarking ROC AUC Evaluation

Test Set Prediction		Decision Tree			Random Forest			SVM tuned			Naive Bayes		
Confusion Matrix		1	2	3	1	2	3	1	2	3	1	2	3
	1	142	105	2	136	114	3	150	98	5	94	133	11
	2	80	373	24	77	382	22	84	383	25	66	341	70
	3	31	142	82	28	124	84	32	130	74	36	137	93
Accuracy		60.86%			61.37%			61.88%			53.82%		

The best classifier is SVM tuned with the highest test set accuracy of **61.88%**.

The worst classifier is Naive Bayes with the lowest test set accuracy of **53.82%**.

Decision Tree	TP	FP	FN	TN	Precision	Recall
Class 1	142	111	107	621	0.5612648221	0.5702811245
Class 2	373	247	104	257	0.6016129032	0.7819706499
Class 3	82	26	173	700	0.7592592593	0.3215686275

In the Decision Tree model, the easiest to recognize is Class 2, with recall 78.2% and precision 60.2%. In contrast, Class 3 is the most challenging, with the lowest recall of 32.15%.

Random Forest	TP	FP	FN	TN	Precision	Recall
Class 1	136	105	117	612	0.5643153527	0.5375494071
Class 2	382	238	99	251	0.6161290323	0.7941787942
Class 3	84	25	152	709	0.7706422018	0.3559322034

For the Random Forest model, Class 2 achieves the highest recall 79.4% and precision 61.61%, while Class 3 remains the lowest recall of 35.6%.

SVM	TP	FP	FN	TN	Precision	Recall
Class 1	150	116	103	612	0.5639097744	0.5928853755
Class 2	383	228	109	261	0.6268412439	0.7784552846
Class 3	74	30	162	715	0.7115384615	0.313559322

The SVM model performs best on Class 2 (precision 62.7%, recall 77.8%), while Class 3 again has the lowest recall at 31.36%.

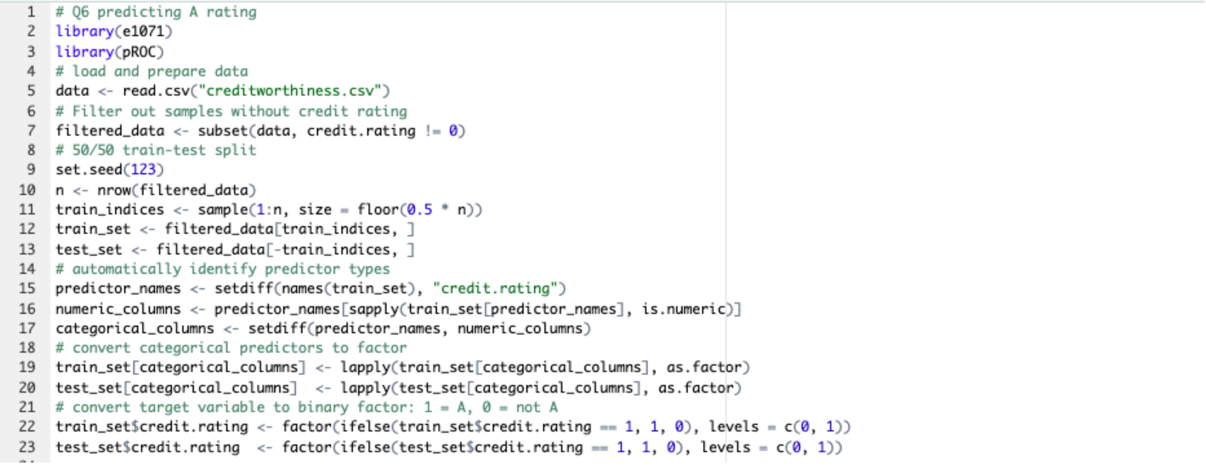
Naive Bayes	TP	FP	FN	TN	Precision	Recall
Class 1	94	102	144	641	0.4795918367	0.3949579832
Class 2	341	270	136	234	0.558101473	0.714884696
Class 3	93	81	173	634	0.5344827586	0.3496240602

In the Naive Bayes model, Class 1 and Class 3 both show relatively low recall, with Class 3 being the weakest of 34.96%. However, Class 2 is still the best classification in terms of comprehensive precision (55.81%) and recall (71.49%).

Overall, **Class 3** is **the hardest to classify for all models**, while Class 2 is consistently the most accurately identified, Class 1 indicates moderate difficulty in accurate prediction.

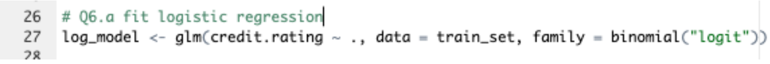
Question 6

(a)Prepare data for fitting logistic regression model



```r
# Q6 predicting A rating
library(e1071)
library(pROC)
# load and prepare data
data <- read.csv("creditworthiness.csv")
# Filter out samples without credit rating
filtered_data <- subset(data, credit.rating != 0)
# 50/50 train-test split
set.seed(123)
n <- nrow(filtered_data)
train_indices <- sample(1:n, size = floor(0.5 * n))
train_set <- filtered_data[train_indices, ]
test_set <- filtered_data[-train_indices, ]
# automatically identify predictor types
predictor_names <- setdiff(names(train_set), "credit.rating")
numeric_columns <- predictor_names[sapply(train_set[predictor_names], is.numeric)]
categorical_columns <- setdiff(predictor_names, numeric_columns)
# convert categorical predictors to factor
train_set[categorical_columns] <- lapply(train_set[categorical_columns], as.factor)
test_set[categorical_columns]  <- lapply(test_set[categorical_columns], as.factor)
# convert target variable to binary factor: 1 = A, 0 = not A
train_set$credit.rating <- factor(ifelse(train_set$credit.rating == 1, 1, 0), levels = c(0, 1))
test_set$credit.rating  <- factor(ifelse(test_set$credit.rating == 1, 1, 0), levels = c(0, 1))
```

Fit logistic regression model:

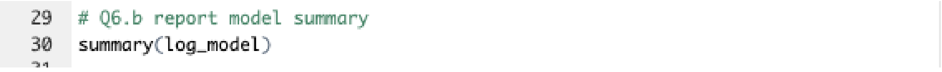


```r
# Q6.a fit logistic regression
log_model <- glm(credit.rating ~ ., data = train_set, family = binomial("logit"))
```

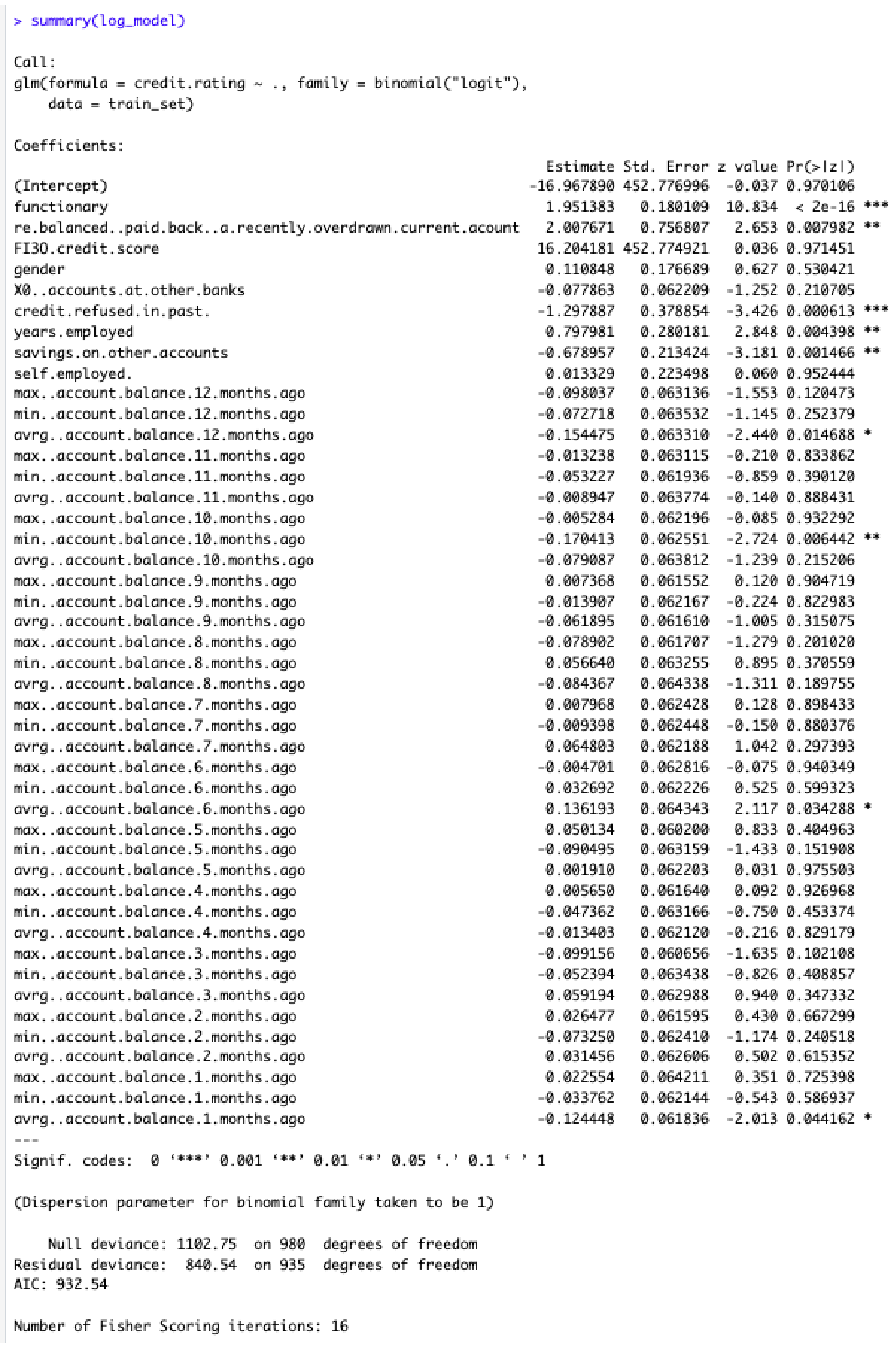
In the logistic regression model, the response variable is defined as I(credit.rating == 1), which evaluates to TRUE for customers with a credit rating of 1 (representing an “A” rating), and FALSE otherwise. This effectively creates a binary classification problem where the target is 1 for “A” ratings and 0 for all other ratings.

The **family = binomial("logit")** argument specifies that the model should use the logistic (logit) link function, making this a logistic regression model. And the model is trained using the train_data dataset to learn the relationship between the predictors and the likelihood of a customer receiving an “A” rating.

(b)summary table of the logistic regression model lift:



```r
# Q6.b report model summary
summary(log_model)
```



```
> summary(log_model)

Call:
glm(formula = credit.rating ~ ., family = binomial("logit"), 
    data = train_set)

Coefficients:
                                                              Estimate Std. Error z value Pr(>|z|)    
(Intercept)                                                 -16.967890 452.776996  -0.037 0.970106    
functionary                                                   1.951383   0.180109  10.834  < 2e-16 ***
re.balanced..paid.back..a.recently.overdrawn.current.acount   2.007671   0.756807   2.653 0.007982 ** 
FI3O.credit.score                                            16.204181 452.774921   0.036 0.971451    
gender                                                        0.110848   0.176689   0.627 0.530421    
X0..accounts.at.other.banks                                  -0.077863   0.062209  -1.252 0.210705    
credit.refused.in.past.                                      -1.297887   0.378854  -3.426 0.000613 ***
years.employed                                                0.797981   0.280181   2.848 0.004398 ** 
savings.on.other.accounts                                    -0.678957   0.213424  -3.181 0.001466 ** 
self.employed.                                                0.013329   0.223498   0.060 0.952444    
max..account.balance.12.months.ago                           -0.098037   0.063136  -1.553 0.120473    
min..account.balance.12.months.ago                           -0.072718   0.063532  -1.145 0.252379    
avrg..account.balance.12.months.ago                          -0.154475   0.063310  -2.440 0.014688 *  
max..account.balance.11.months.ago                           -0.013238   0.063115  -0.210 0.833862    
min..account.balance.11.months.ago                           -0.053227   0.061936  -0.859 0.390120    
avrg..account.balance.11.months.ago                          -0.008947   0.063774  -0.140 0.888431    
max..account.balance.10.months.ago                           -0.005284   0.062196  -0.085 0.932292    
min..account.balance.10.months.ago                           -0.170413   0.062551  -2.724 0.006442 ** 
avrg..account.balance.10.months.ago                          -0.079087   0.063812  -1.239 0.215206    
max..account.balance.9.months.ago                             0.007368   0.061552   0.120 0.904719    
min..account.balance.9.months.ago                            -0.013907   0.062167  -0.224 0.822983    
avrg..account.balance.9.months.ago                           -0.061895   0.061610  -1.005 0.315075    
max..account.balance.8.months.ago                            -0.078902   0.061707  -1.279 0.201020    
min..account.balance.8.months.ago                             0.056640   0.063255   0.895 0.370559    
avrg..account.balance.8.months.ago                           -0.084367   0.064338  -1.311 0.189755    
max..account.balance.7.months.ago                             0.007968   0.062428   0.128 0.898433    
min..account.balance.7.months.ago                            -0.009398   0.062448  -0.150 0.880376    
avrg..account.balance.7.months.ago                            0.064803   0.062188   1.042 0.297393    
max..account.balance.6.months.ago                            -0.004701   0.062816  -0.075 0.940349    
min..account.balance.6.months.ago                             0.032692   0.062226   0.525 0.599323    
avrg..account.balance.6.months.ago                            0.136193   0.064343   2.117 0.034288 *  
max..account.balance.5.months.ago                             0.050134   0.060200   0.833 0.404963    
min..account.balance.5.months.ago                            -0.090495   0.063159  -1.433 0.151908    
avrg..account.balance.5.months.ago                            0.001910   0.062203   0.031 0.975503    
max..account.balance.4.months.ago                             0.005650   0.061640   0.092 0.926968    
min..account.balance.4.months.ago                            -0.047362   0.063166  -0.750 0.453374    
avrg..account.balance.4.months.ago                           -0.013403   0.062120  -0.216 0.829179    
max..account.balance.3.months.ago                            -0.099156   0.060656  -1.635 0.102108    
min..account.balance.3.months.ago                            -0.052394   0.063438  -0.826 0.408857    
avrg..account.balance.3.months.ago                            0.059194   0.062988   0.940 0.347332    
max..account.balance.2.months.ago                             0.026477   0.061595   0.430 0.667299    
min..account.balance.2.months.ago                            -0.073250   0.062410  -1.174 0.240518    
avrg..account.balance.2.months.ago                            0.031456   0.062606   0.502 0.615352    
max..account.balance.1.months.ago                             0.022554   0.064211   0.351 0.725398    
min..account.balance.1.months.ago                            -0.033762   0.062144  -0.543 0.586937    
avrg..account.balance.1.months.ago                           -0.124448   0.061836  -2.013 0.044162 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1102.75  on 980  degrees of freedom
Residual deviance:  840.54  on 935  degrees of freedom
AIC: 932.54

Number of Fisher Scoring iterations: 16
```

Estimate indicates the estimated coefficient for each predictor:

- **A positive value** means an increase in the predictor increases the log-odds of being in Class 1 that receiving credit rating A.
- **A negative value** means an increase in the predictor decreases the log-odds.

Std. Error measures the variability (uncertainly) in the coefficient estimate, larger values indicate less accuracy.

Z value: The standardized test statistic for the hypothesis test of each coefficient (Estimate / Std. Error).

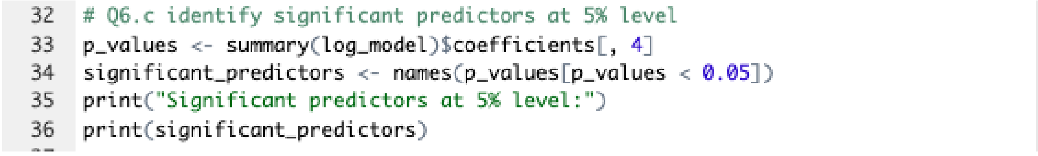
Pr(>|z|) also known as p-value, is the most critical statistical significance test result is that value < 0.05 is a significant feature, the smaller the value, the better.

Significance codes: Asterisks (*) indicate which attributes have a statistically significant effect on the response after controlling for other predictors in the model, such as functionary and credit.refused.in. past etc.

Model fit statistics:

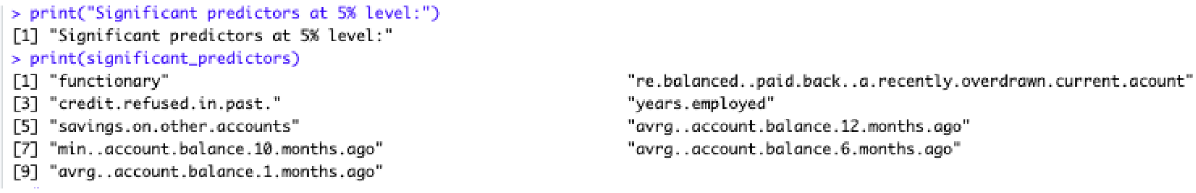
The model converged after 16 Fisher scoring iterations. The Null Deviance was 1102.75 (on 980 degrees of freedom), and the Residual Deviance was 840.54 (on 935 degrees of freedom). The Akaike Information Criterion (AIC) was 932.54.

(c) Significant predictors at 5% level



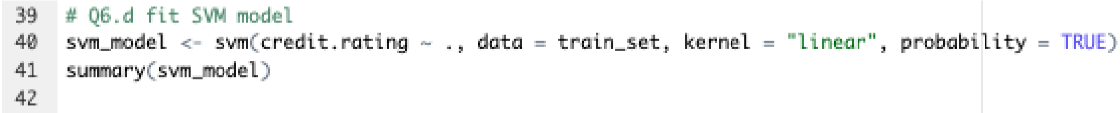
```r
# Q6.c identify significant predictors at 5% level
p_values <- summary(log_model)$coefficients[, 4]
significant_predictors <- names(p_values[p_values < 0.05])
print("Significant predictors at 5% level:")
print(significant_predictors)
```

If the **p-value** of a variable is **less than 0.05,** that is, the variable is a significant predictor at 5% level in the logistic regression model. The results are 9 significant predictors at 5% level as below shown:

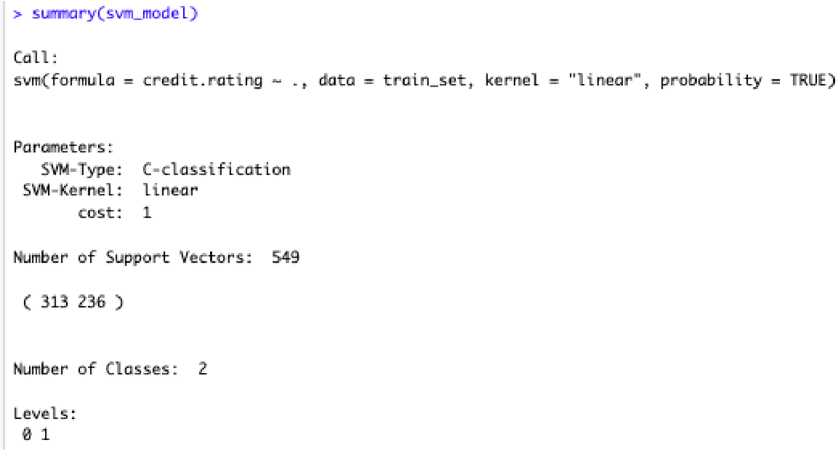


```
> print("Significant predictors at 5% level:")
[1] "Significant predictors at 5% level:"
> print(significant_predictors)
[1] "functionary"                                        "re.balanced..paid.back..a.recently.overdrawn.current.acount"
[3] "credit.refused.in.past."                            "years.employed"
[5] "savings.on.other.accounts"                          "avrg..account.balance.12.months.ago"
[7] "min..account.balance.10.months.ago"                 "avrg..account.balance.6.months.ago"
[9] "avrg..account.balance.1.months.ago"
```

(d) Fit an SVM model



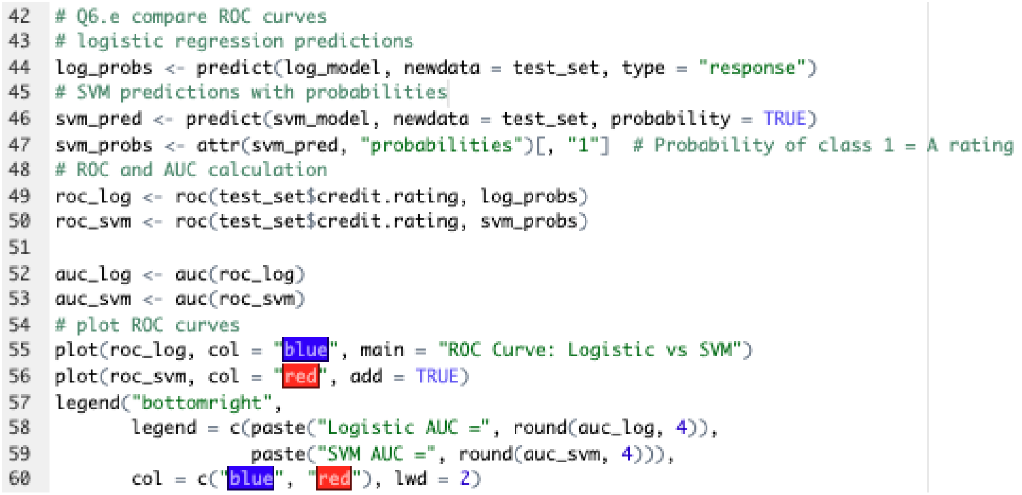
```r
# Q6.d fit SVM model
svm_model <- svm(credit.rating ~ ., data = train_set, kernel = "linear", probability = TRUE)
summary(svm_model)
```



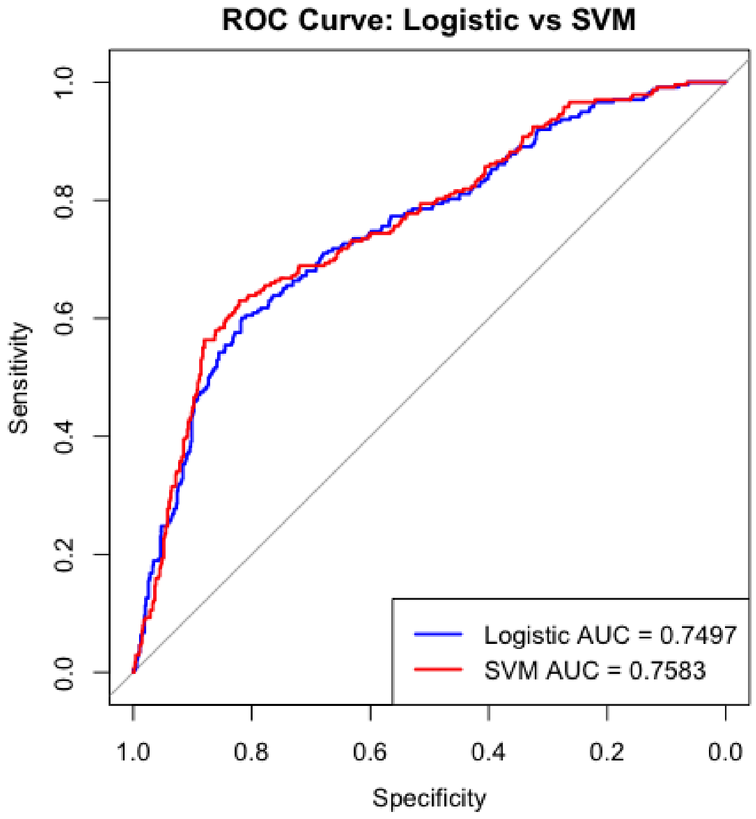
```
> summary(svm_model)

Call:
svm(formula = credit.rating ~ ., data = train_set, kernel = "linear", probability = TRUE)


Parameters:
   SVM-Type:  C-classification
 SVM-Kernel:  linear
       cost:  1

Number of Support Vectors:  549

 ( 313 236 )


Number of Classes:  2

Levels:
 0 1
```

A linear SVM model was fitted using a linear kernel and cost = 1, with 549 support vectors (313 for Class A and 236 for Class “not A”).

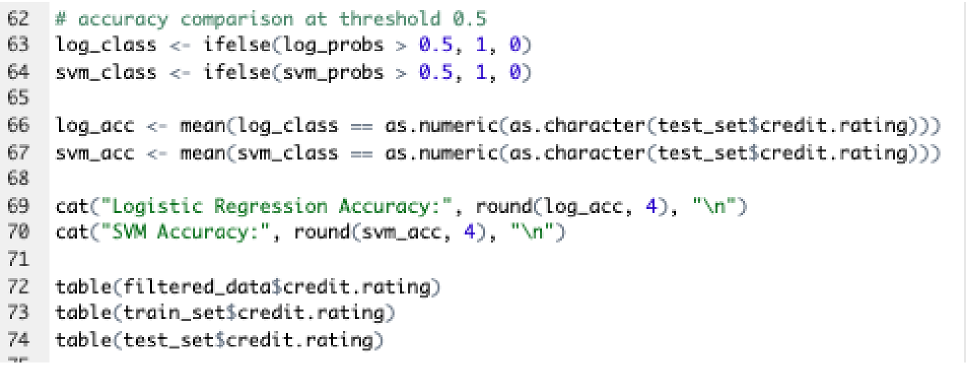
(e) ROC comparison between Logistic Regression and SVM



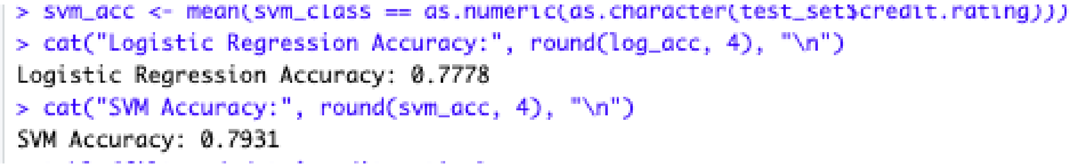
```
# Q6.e compare ROC curves
# logistic regression predictions
log_probs <- predict(log_model, newdata = test_set, type = "response")
# SVM predictions with probabilities
svm_pred <- predict(svm_model, newdata = test_set, probability = TRUE)
svm_probs <- attr(svm_pred, "probabilities")[, "1"]  # Probability of class 1 = A rating
# ROC and AUC calculation
roc_log <- roc(test_set$credit.rating, log_probs)
roc_svm <- roc(test_set$credit.rating, svm_probs)

auc_log <- auc(roc_log)
auc_svm <- auc(roc_svm)
# plot ROC curves
plot(roc_log, col = "blue", main = "ROC Curve: Logistic vs SVM")
plot(roc_svm, col = "red", add = TRUE)
legend("bottomright",
       legend = c(paste("Logistic AUC =", round(auc_log, 4)),
                  paste("SVM AUC =", round(auc_svm, 4))),
       col = c("blue", "red"), lwd = 2)
```



The ROC chart above compares the binary classification performance of the logistic regression model and the SVM model on the test set. The logistic regression model achieved an AUC of 0.75, whereas the SVM model achieved an AUC of 0.76, indicating that both models perform reasonably well. However, the SVM model shows a slightly better trade-off between sensitivity and specificity, particularly at lower false positive rates.



```
# accuracy comparison at threshold 0.5
log_class <- ifelse(log_probs > 0.5, 1, 0)
svm_class <- ifelse(svm_probs > 0.5, 1, 0)

log_acc <- mean(log_class == as.numeric(as.character(test_set$credit.rating)))
svm_acc <- mean(svm_class == as.numeric(as.character(test_set$credit.rating)))

cat("Logistic Regression Accuracy:", round(log_acc, 4), "\n")
cat("SVM Accuracy:", round(svm_acc, 4), "\n")

table(filtered_data$credit.rating)
table(train_set$credit.rating)
table(test_set$credit.rating)
```



```
> svm_acc <- mean(svm_class == as.numeric(as.character(test_set$credit.rating)))
> cat("Logistic Regression Accuracy:", round(log_acc, 4), "\n")
Logistic Regression Accuracy: 0.7778
> cat("SVM Accuracy:", round(svm_acc, 4), "\n")
SVM Accuracy: 0.7931
```

At a 0.5 threshold, SVM also achieved higher accuracy 79.31% compared to logistic regression 77.78%, consistent with its slightly superior AUC.

This result suggests that the SVM classifier has better discriminative ability in this dataset, which is consistent with its strength in finding optimal margins and handling borderline cases. However, the logistic model provides higher interpretability, in particular to understand each predictor variable.

The final model choice between these models would depend on whether predictive performance or model transparency is prioritized in practice.