MCDA5580 Assignment 2

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Executive Summary

We are given dataset of customer feedback regarding the desirability of buying the car with features like safety, price etc. We explored supervised classification algorithms to develop models to predict desirability of buying cars given their features. We evaluated the model performance using different hyperparameters and performance metrics. The final selected model is the model created from Caret package with 98% accuracy.

Our ultimate goal is to deploy optimized model as a recommendation system on the website of car dealers in the Halifax area. Also, collect online feedback from customers of dealers and use it to evaluate and update the model. However, the current result tends to have overfitting problem which may affect the ability of describing actual customer behaviors. So, to fine tune model with a larger data set is suggested before deploying the final solution.

Objectives

The main **o**bjective of this process is to create a data model to classify the datasets into different classes using the results obtained and group together as different sets for easy understanding. This will create a model which will have high accuracy and less error. The obtained result will give clarity in determining the best and fewer performing categories which may help to understand the user preference. This will also provide an overview of where the growth of the organization is affected. Overall, the aim of the model is to give a quality result for identifying where the improvement should be made to increase the future result.

There are clear classified results ("shouldBuy") in this problem, and it had type of classes > 2. Therefore, supervised classification models which support multiple class should be selected. In report, Decision Tree & Random Forecast models will be used, which have advantages of having good predictive power (especially for Random Forest), relatively easy to build and tune and the result more able to be visualized.

Data Analysis

Dataset has 1798 rows with 6 independent and 1 dependent variable. All the data is categorical. There are no missing or invalid values.

Below is description of independent variables. All the data is evenly distributed across different categories.

price - 4 categories (low, med, high, vhigh)

maintenance - 4 categories (low, med, high, vhigh)

doors - 4 categories (2, 3, 4, 5more)

seats - 3 categories (2, 4, more)

storage - 3 categories (small, med, big)

safety - 3 categories (low, med, high)

shouldBuy is dependent and categorical variable. It can take 4 values which describe desirability of buying the car in ascending order.

unacc - Unacceptable (don't buy)

acc - Acceptable to buy

good - Good to buy

vgood - Very good to buy

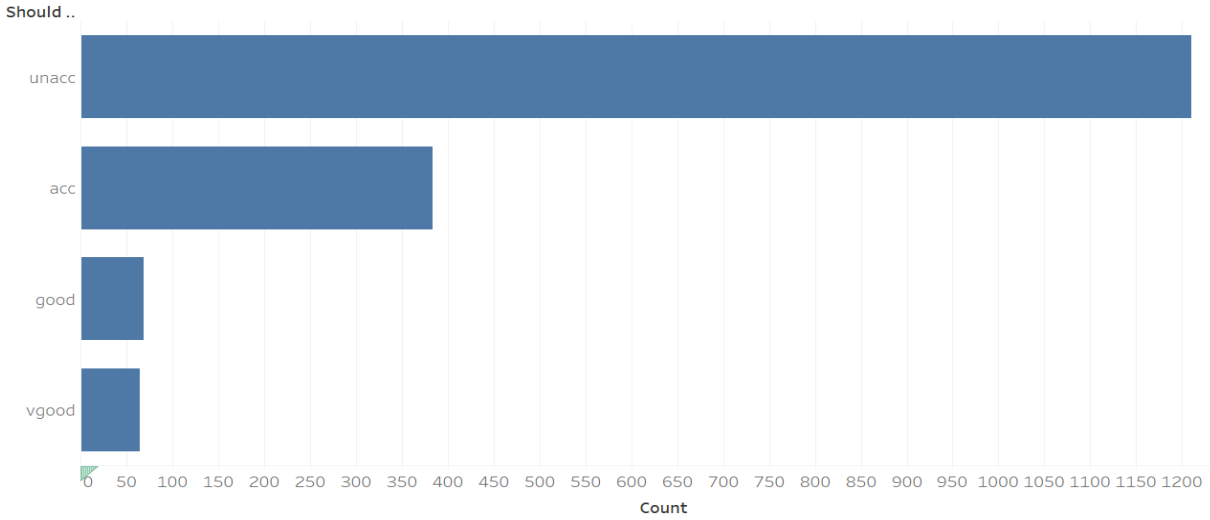


Figure 1 Count Plot - Output Classes

Correlation - Contingency matrix for each combination of independent variables is having same values which rules out any possibility of any correlation. No further analysis or plotting is required in this regard.

Screen shot of price vs safety is shown below:

```
[1] "Contingency matrix of  price  vs  safety"

       high low med
high    144 144 144
low     144 144 144
med     144 144 144
vhigh   144 144 144
```

Design/ Methodology/ Approach

Overview

Decision Tree & Random Forecast models is used in this report, differences between Decision Tree & Random Forecast models are the result of Random Forecast is generated from the result a set of decision trees. Compare with single decision tree, it reduces overfitting and improved accuracy. The two models will be implemented by the rpart (for Decision Tree) and randomForest (for Random Forecast) package in R. In addition, Caret package will also be used to cross checking which is a comprehensive framework for model development in R. Finally, the Area Under Curve (AUC) value will be used to evaluate the performance of the tested models.

Decision tree Analysis

Decision Tree Algorithm is one of the classification algorithms for understanding the dataset and predicting the future results by recursively partitioning the input dataset into smaller sets. Since the decision trees visualization is effective which will enable the user to view and understand how the predictions are obtained by the algorithm. They provide results fast that will make them easy to train. They are good in handling both numerical and categorical datasets.

Methodology

1. Dataset has been loaded and split into two parts namely, Training set (80%) and Testing set (80%).

```
head(carData)
```

```
price maintenance doors seats storage safety shouldBuy1 vhigh       vhigh
2     2   small    low     unacc2 vhigh       vhigh     2     2   small
med     unacc3 vhigh       vhigh     2     2   small   high     unacc4 vhigh
vhigh     2     2     med    low     unacc5 vhigh       vhigh     2     2
med    med     unacc6 vhigh       vhigh     2     2     med   high     unacc
```

2. Decision tree is formed using rpart function with minsplit value as 6 for control parameter. Training set is used for creating the decision tree.

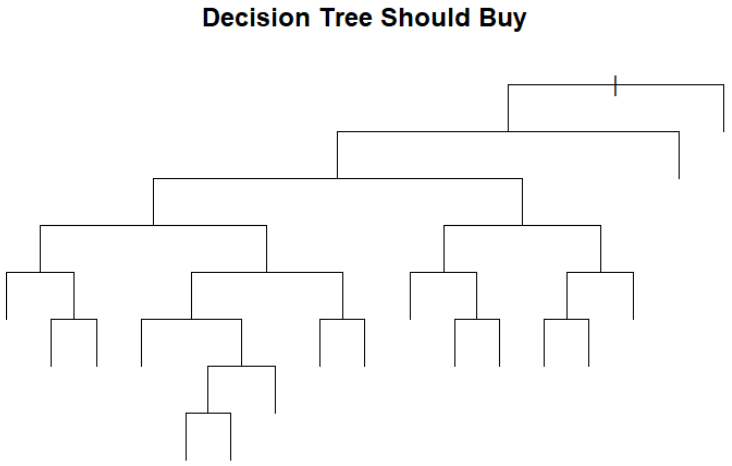


Figure 2 Decision Tree

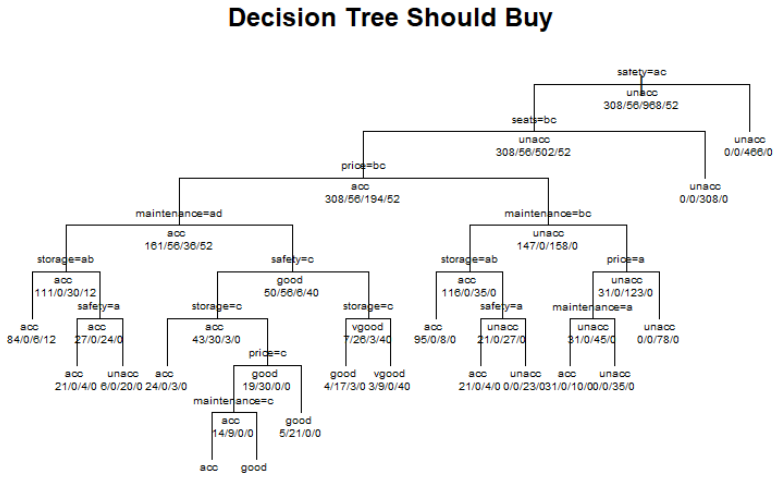
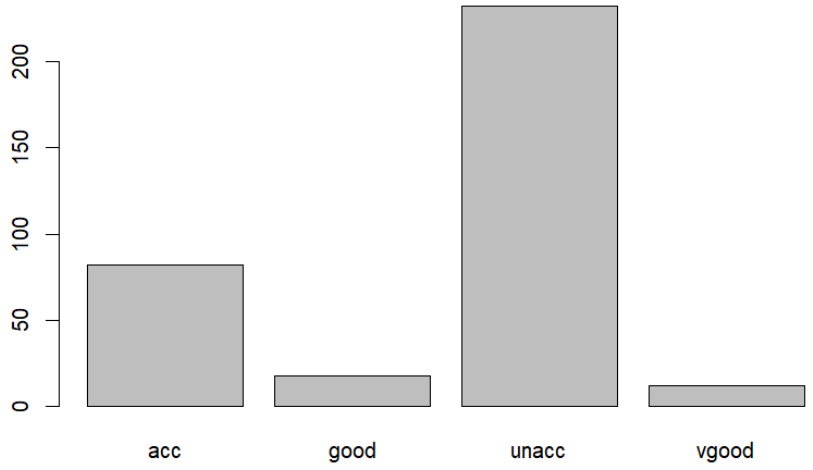


Figure 3 Decision Tree with Labels

Rules of Decision Tree

```
shouldBuy   acc good unac vgoo
      acc [ .72  .00  .28  .00] when seats is 4 or more & safety is high or med & price is          high & maintenance is          high
      acc [ .80  .00  .20  .00] when seats is 4 or more & safety is         med & price is high or vhigh & maintenance is    low or med & storage is big or med
      acc [ .81  .00  .09  .10] when seats is 4 or more & safety is high or med & price is    low or med & maintenance is high or vhigh & storage is big or med
      acc [ .85  .00  .15  .00] when seats is 4 or more & safety is         med & price is    low or med & maintenance is    low or med & storage is      small
      acc [ .87  .00  .13  .00] when seats is 4 or more & safety is        high & price is    low or med & maintenance is high or vhigh & storage is      small
      acc [ .96  .00  .04  .00] when seats is 4 or more & safety is        high & price is high or vhigh & maintenance is    low or med
      acc [1.00  .00  .00  .00] when seats is 4 or more & safety is         med & price is          med & maintenance is          med & storage is big or med
     good [ .19  .67  .14  .00] when seats is 4 or more & safety is        high & price is    low or med & maintenance is    low or med & storage is      small
     good [ .18  .82  .00  .00] when seats is 4 or more & safety is         med & price is          low & maintenance is          med & storage is big or med
     good [ .17  .83  .00  .00] when seats is 4 or more & safety is         med & price is    low or med & maintenance is          low & storage is big or med
    unacc [ .19  .00  .81  .00] when seats is 4 or more & safety is         med & price is    low or med & maintenance is high or vhigh & storage is      small
    unacc [ .00  .00 1.00  .00] when seats is 4 or more & safety is         med & price is high or vhigh & maintenance is    low or med & storage is      small
    unacc [ .00  .00 1.00  .00] when seats is 4 or more & safety is high or med & price is          high & maintenance is         vhigh
    unacc [ .00  .00 1.00  .00] when seats is 4 or more & safety is high or med & price is         vhigh & maintenance is high or vhigh
    unacc [ .00  .00 1.00  .00] when seats is 4 or more & safety is         low
    unacc [ .00  .00 1.00  .00] when seats is         2
    vgood [ .06  .15  .00  .79] when seats is 4 or more & safety is        high & price is    low or med & maintenance is    low or med & storage is big or med
```

3. Minsplit is decided based on the reached AUC result with the best closer value.
4. Car prediction is done using decision tree and test data with predict () method
5. Predict data is created for both class and problem.



6. Confusion matrix and statistics (Accuracy, Sensitivity (Recall), Specificity etc.) are created based on test data and predicted class results.

```
Confusion Matrix and Statistics

          Reference
Prediction unacc acc good vgood
     unacc   233   3    0     0
     acc       9  69    0     2
     good      0   3   11     0
     vgood     0   1    2    11

Overall Statistics

               Accuracy : 0.9419
                 95% CI : (0.9116, 0.9641)
    No Information Rate : 0.7035
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.8744

 Mcnemar's Test P-Value : NA

Statistics by Class:

                     Class: unacc Class: acc Class: good Class: vgood
Sensitivity                0.9628     0.9079     0.84615      0.84615
Specificity                0.9706     0.9590     0.99094      0.99094
Pos Pred Value             0.9873     0.8625     0.78571      0.78571
Neg Pred Value             0.9167     0.9735     0.99394      0.99394
Prevalence                 0.7035     0.2209     0.03779      0.03779
Detection Rate             0.6773     0.2006     0.03198      0.03198
Detection Prevalence       0.6860     0.2326     0.04070      0.04070
Balanced Accuracy          0.9667     0.9334     0.91855      0.91855
```

7. Multiclass ROC is created using test data and Problem Prediction result

8. Using Multiclass ROC result, Area under Curve is determined

```
sum(diag(treeCarCM)/sum(treeCarCM))[1] 0.9505814
auc(roc.multi)Multi-class area under the curve: 0.8878
```

9. ROC graph is plotted for each individual classes namely, ACC, UNACC, GOOD, VGOOD

.

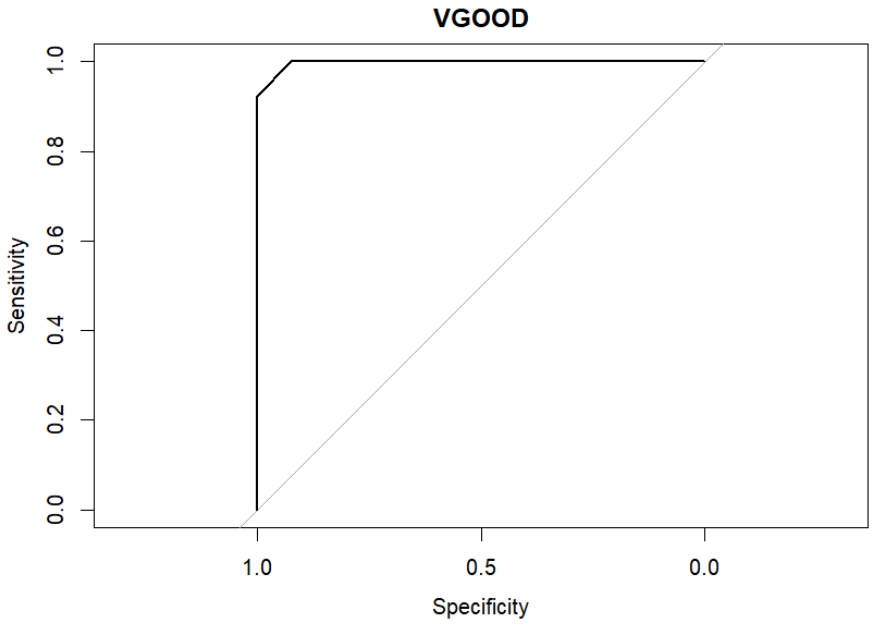


Figure 4 ROC Plot

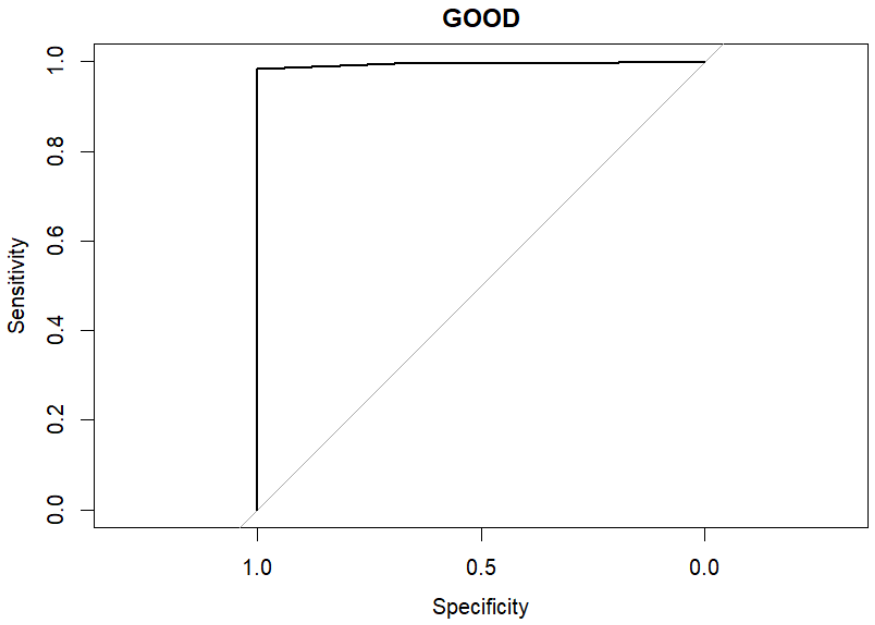


Figure 5 ROC Plot

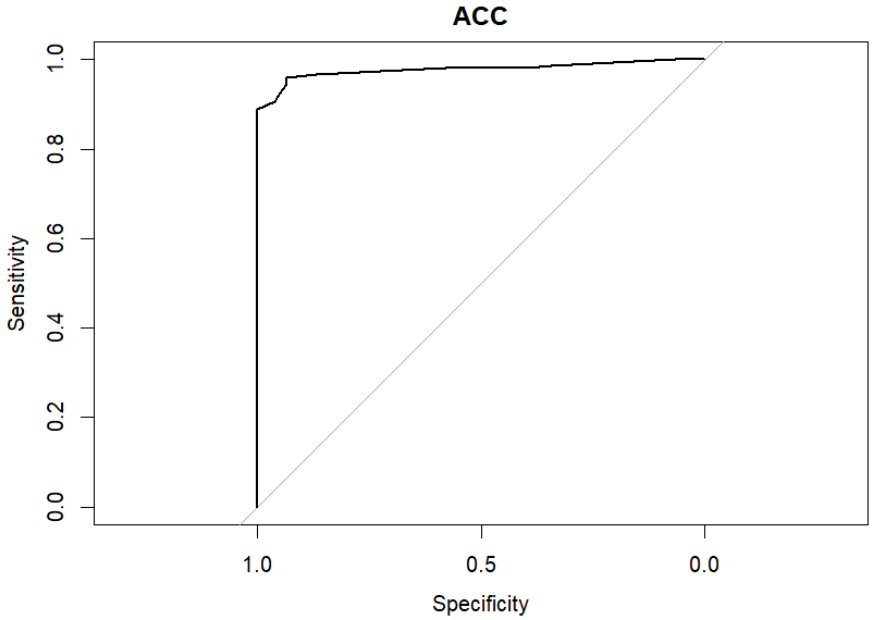


Figure 6 ROC Plot

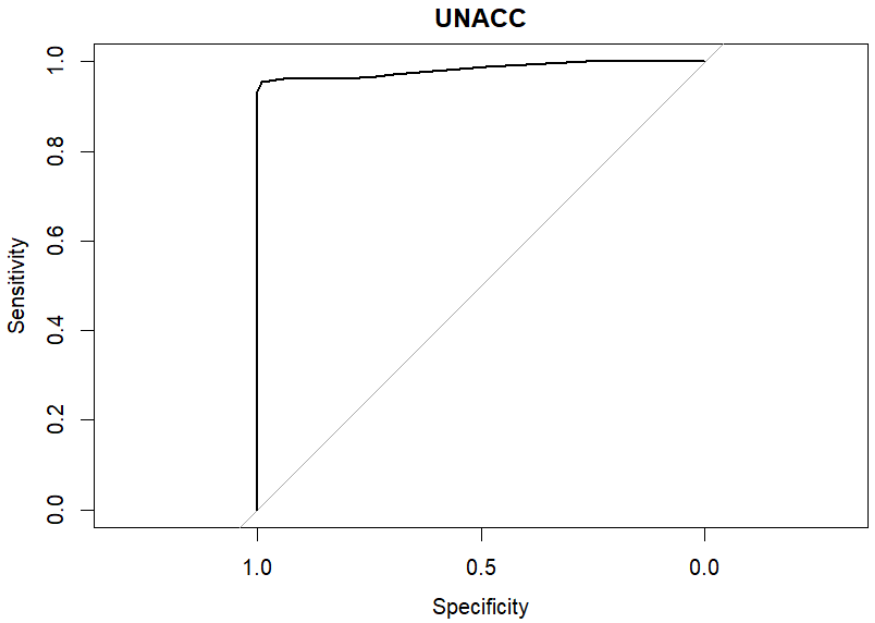


Figure 7 ROC Plot

Summary

Final model gave accuracy of 94.19% and AUC of 0.8878 with parameter minsplit=6

Random Forest Analysis

Random Forest algorithm is derived from decision tree algorithm. It contains a collection of decision trees trained on random subsets of features and observations and produce the final result by average the predictions of all the trees.

Compare with original decision tree algorithm, it has advantage of lesser chance to overfit data and better to handle smaller data set. However, it lose the interpretability of result but generally yield a better performance compared with a single decision tree. It is the reason to practice Random Forest algorithm here to discover potential performance gain of prediction model.

Methodology

- Data handling

Data will be split into training (80 %) and testing (20%) set.

- Hyperparameter tuning

  "mtry" parameter

  It controls the number of randomly selected features that are used to determine the best split at each node. i.e., the level of fitting of the algorithm.

  tuneRF() is used in tuning the parameter:

```
> model <- tuneRF(train[,1:6], train[,7] , mtryStart = 2)
mtry = 2  OOB error = 5.56%
Searching left ...
mtry = 1        OOB error = 26.45%
-3.753247 0.05
Searching right ...
mtry = 4        OOB error = 2.75%
0.5064935 0.05
mtry = 6        OOB error = 2.67%
0.02631579 0.05
```

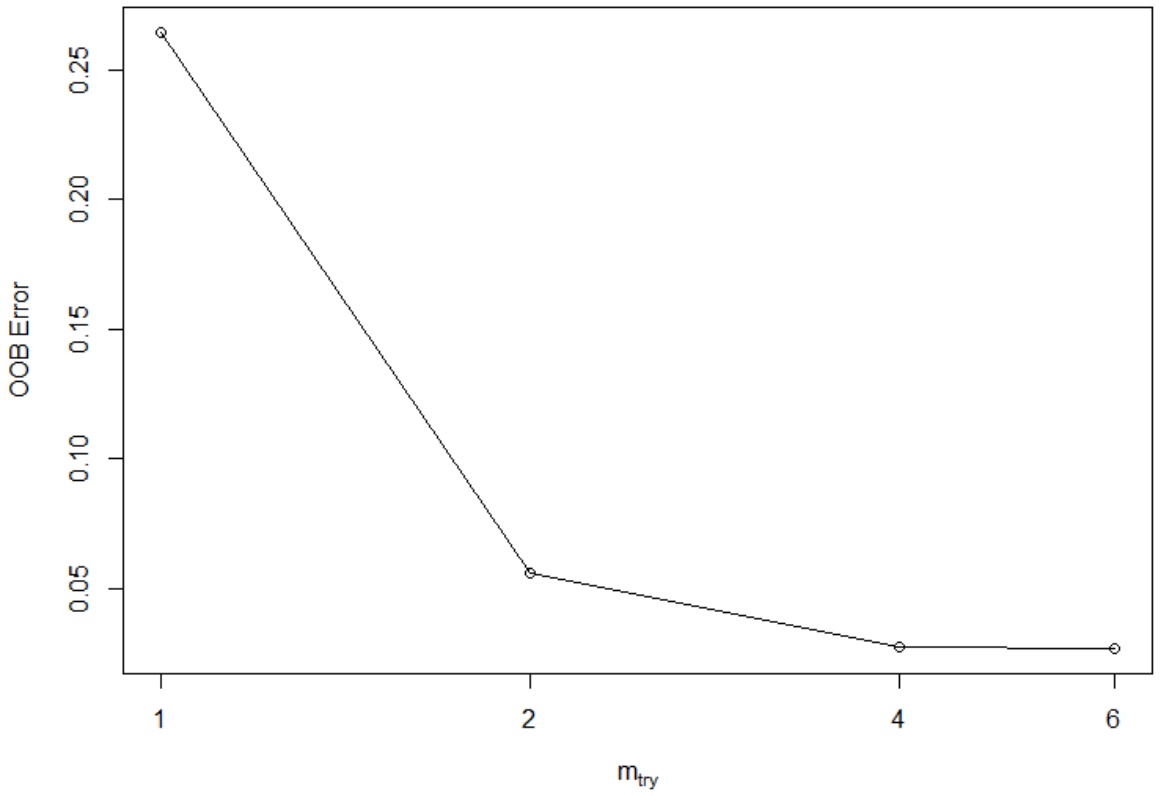


Figure 8 Error Plot vs mtry

We see mtry = 6 have the lowest OOB Error, so it is the optimal value.

- "nodesize" parameter

This parameter specifies the minimum of terminal nodes in the tree. Smaller "nodesize" value results higher predictive accuracy but may cause overfitting.

Random Forest models with different setting are built and tried to predict data in the test data set. The table above contains the confusion matrices and accuracy of these models. We can see node size =1 have the best accuracy, so it will become the optimal parameter.

Node size = 1

```
> rfCM

rfp      unacc acc good vgood
  unacc    241   0    0     0
  acc        1  76    2     0
  good       0   0   11     0
  vgood      0   0    0    13
> sum(diag(rfCM))/sum(rfCM)
[1] 0.9912791
```

Node size = 5

```
> rfCM

rfp      unacc acc good vgood
  unacc    241   1    2     0
  acc        1  74    1     0
  good       0   1   10     0
  vgood      0   0    0    13
> sum(diag(rfCM))/sum(rfCM)
[1] 0.9825581
```

Node size = 10

```
> rfCM

rfp      unacc acc good vgood
  unacc    241   2    2     0
  acc        1  71    0     0
  good       0   3   11     0
  vgood      0   0    0    13
> sum(diag(rfCM))/sum(rfCM)
[1] 0.9767442
```

Optimal model

The hyperparameter tuning yield mtry = 6 and node size = 1 the optimal value for the random forest model. Here are the details of model:

Confusion Matrix and Statistics (Accuracy, Sensitivity (Recall), Specificity etc.)

```
Confusion Matrix and Statistics

          Reference
Prediction unacc acc good vgood
     unacc   238   0    0     0
     acc       4  72    0     0
     good      0   3   13     0
     vgood     0   1    0    13

Overall Statistics

               Accuracy : 0.9767
                 95% CI : (0.9547, 0.9899)
    No Information Rate : 0.7035
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.9496

 Mcnemar's Test P-Value : NA

Statistics by Class:

                     Class: unacc Class: acc Class: good Class: vgood
Sensitivity                0.9835     0.9474     1.00000      1.00000
Specificity                1.0000     0.9851     0.99094      0.99698
Pos Pred Value             1.0000     0.9474     0.81250      0.92857
Neg Pred Value             0.9623     0.9851     1.00000      1.00000
Prevalence                 0.7035     0.2209     0.03779      0.03779
Detection Rate             0.6919     0.2093     0.03779      0.03779
Detection Prevalence       0.6919     0.2209     0.04651      0.04070
Balanced Accuracy          0.9917     0.9662     0.99547      0.99849
```

Variable Importance

```
> importance(rf)
            MeanDecreaseGini
price              117.93927
maintenance        140.85134
doors               34.76179
seats              112.18903
storage             67.98200
safety             158.85180
```

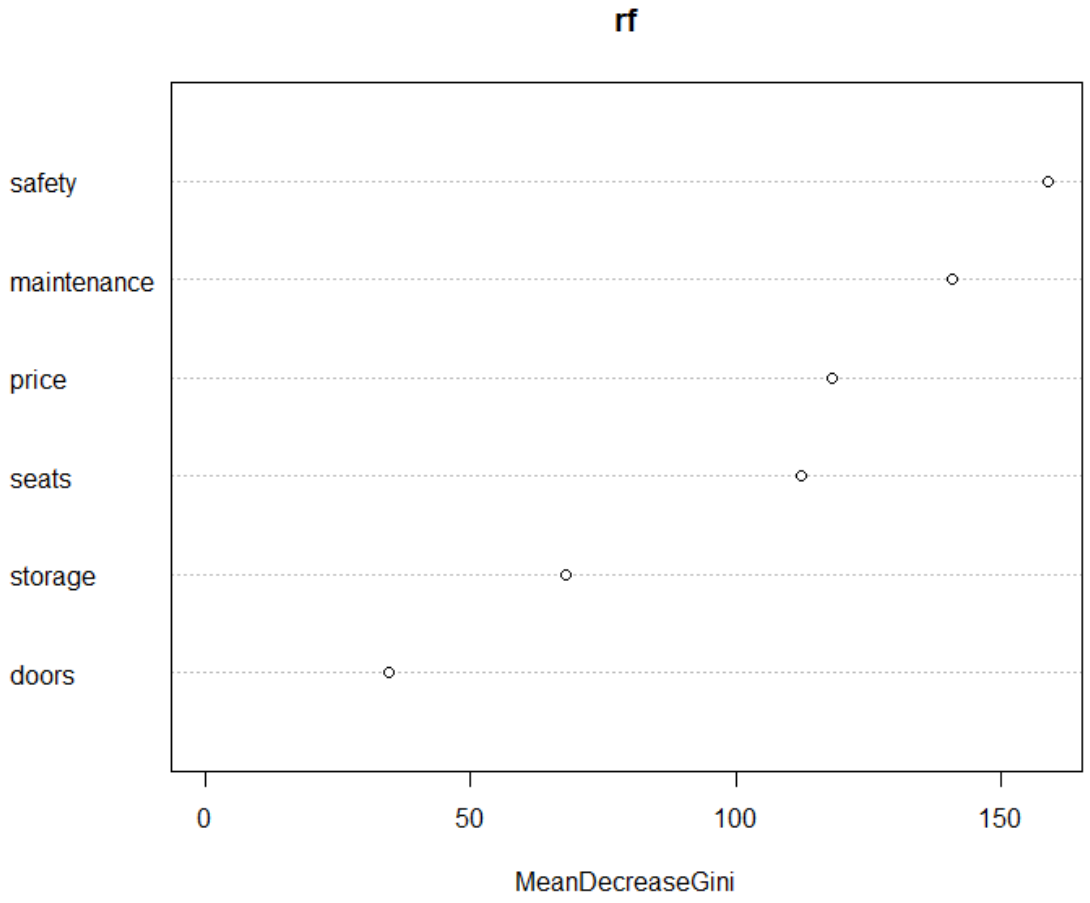


Figure 9 Variable Importance

Plot of a Single Tree in the Random Forecast model

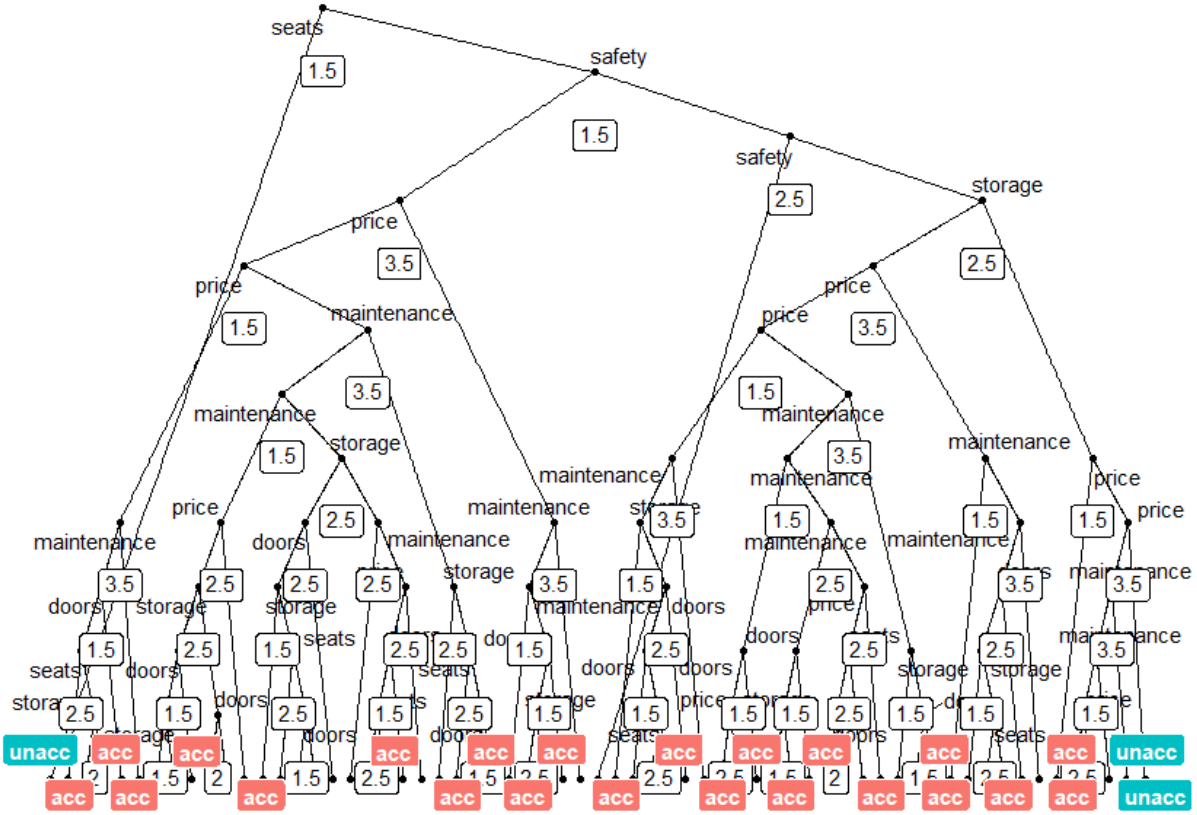


Figure 10 Sample Tree Diagram

ROC (Receiver Operating Characteristics) Curve

ROC for Unacc Class

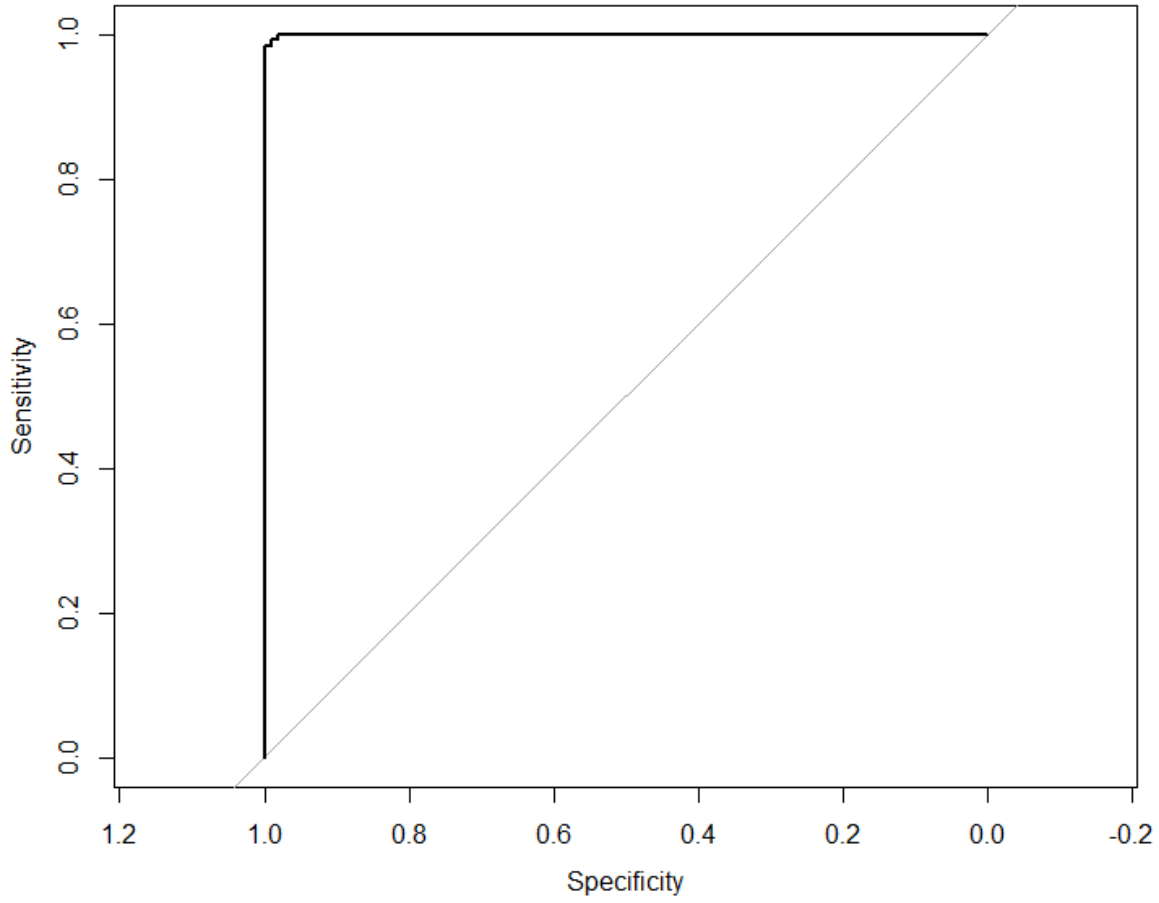


Figure 11 ROC Plot

ROC for Acc Class

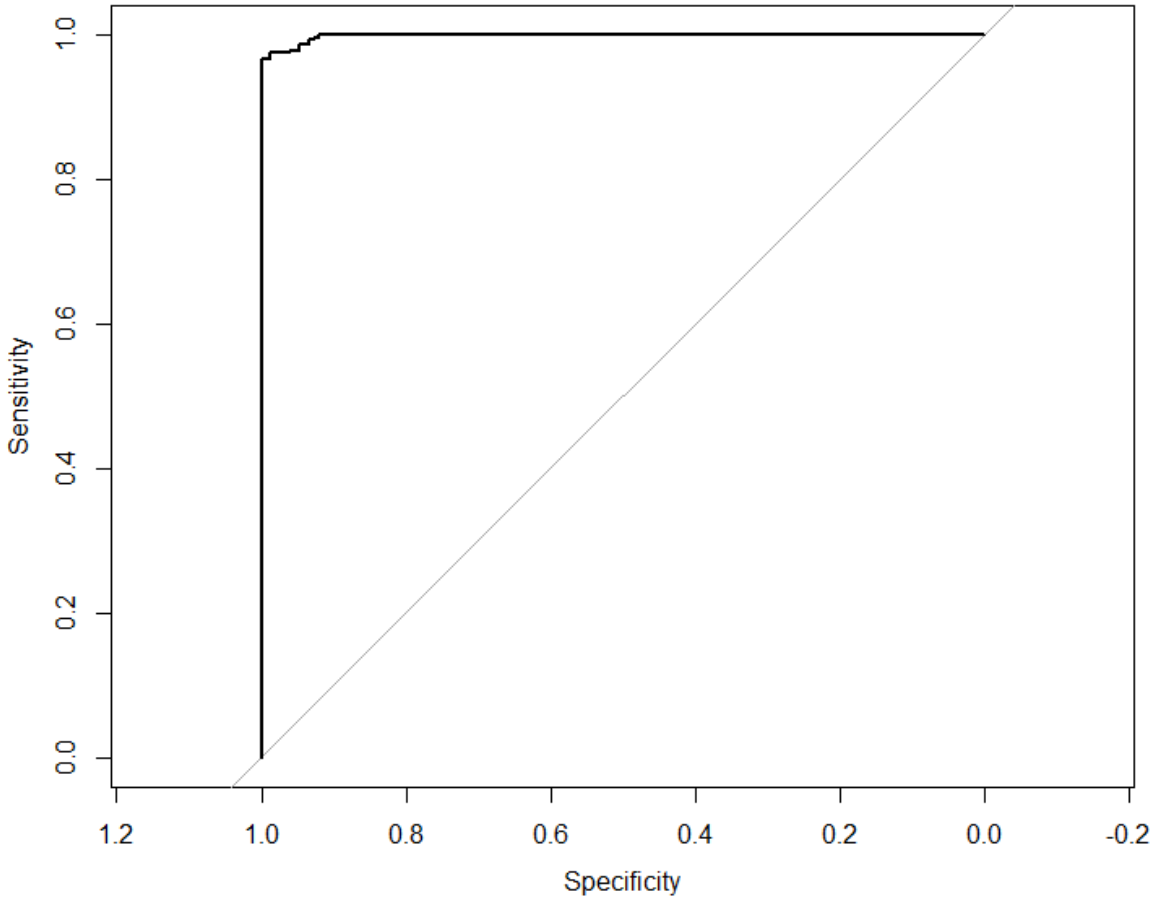


Figure 12 ROC Plot

ROC for Good Class

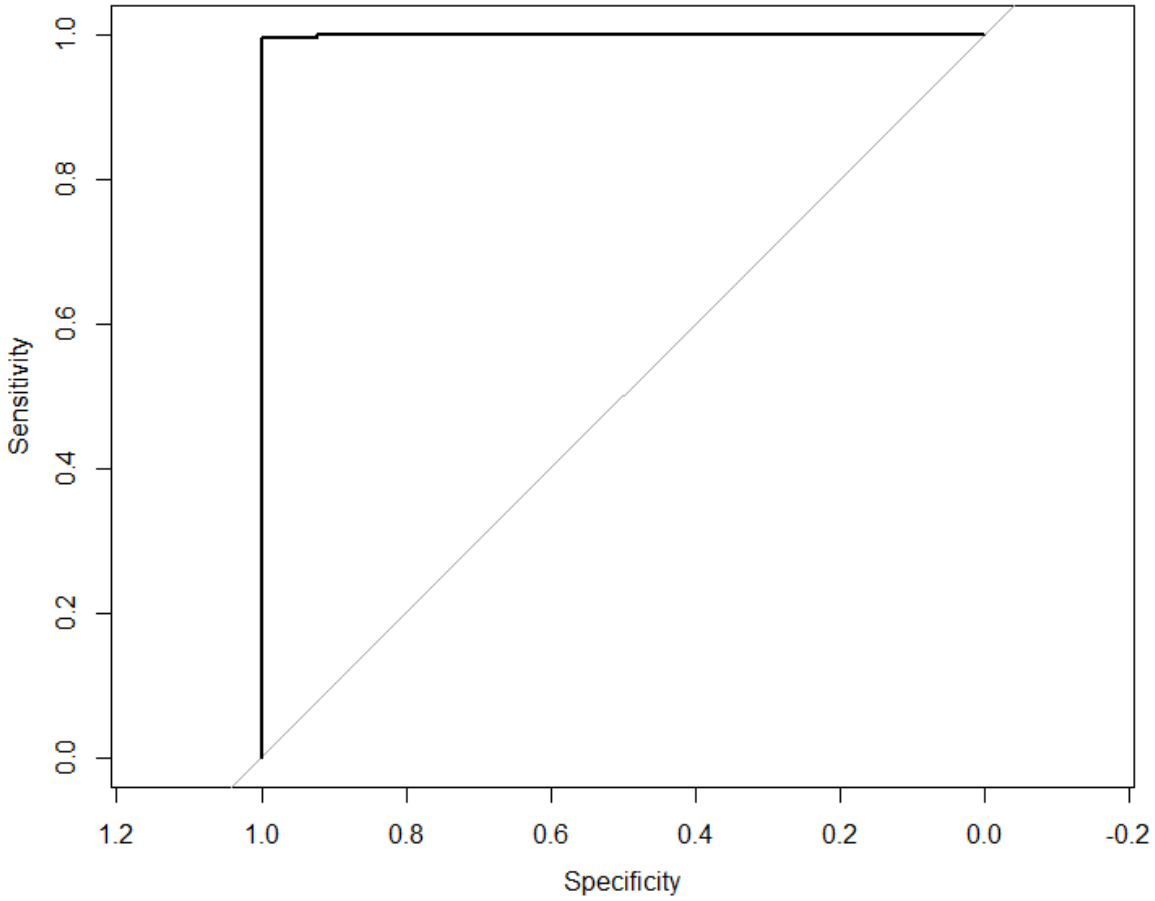


Figure 13 ROC Plot

ROC for Vgood Class

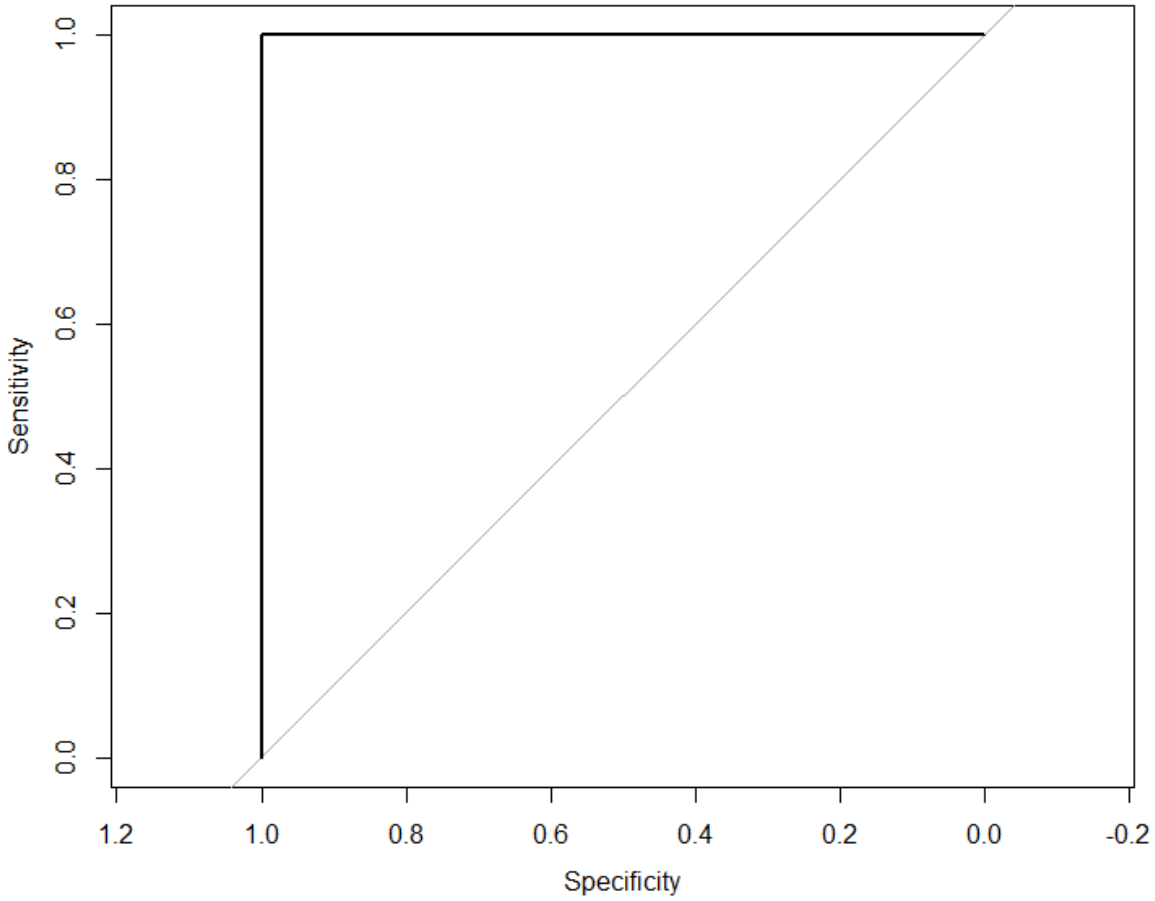


Figure 14 ROC Plot

AUC (Area under Curve)

```
> roc.multi$auc
Multi-class area under the curve: 0.9921
```

Summary

Final model gave accuracy of 97.67% and AUC of 0.9921 with parameters mtry=6, nodesizes =1

Caret (Classification and Regression Training)

Caret is versatile package in R which has lot of tools for

- data splitting
- pre-processing
- feature selection
- model tuning using resampling
- variable importance estimation

This package provides a good interface to perform tasks like parameter tuning and variable importance. Hyperparameter tuning is done using grid search where list of parameters and its values are given in matrix, and it fits the model with all combinations of parameters and then evaluates the best amongst them.

Random forest algorithm in this package allows us to tune only mtry parameter. But it can be customized to tune other features as well. We used this customization approach to tune ntree, minsplit.

Methodology

- Data handling

Data will be split into training (80 %) and testing (20%) set.

- Hyperparameter tuning

Below is the plot of "Accuracy" for mtry, ntree and minsplit combination:

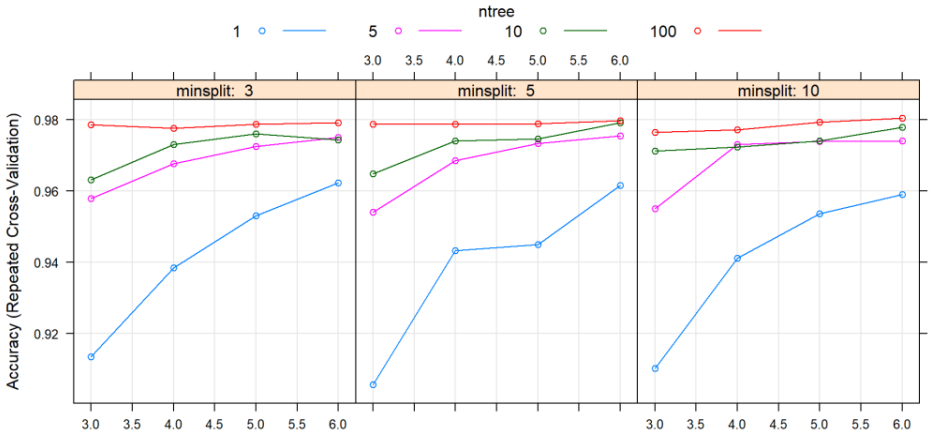


Figure 15 Tuning Plot

Optimal model chosen in the grid search had parameters mtry = 6, ntree = 100, maxdepth = 5 and minsplit = 10.

Variable importance plot for the model:

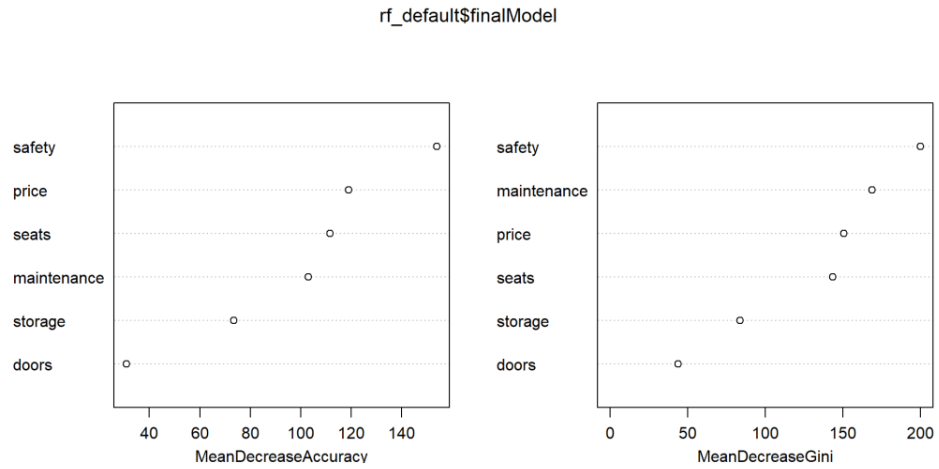


Figure 16 Variable Importance

ROC plot for the final model:

Unacc class

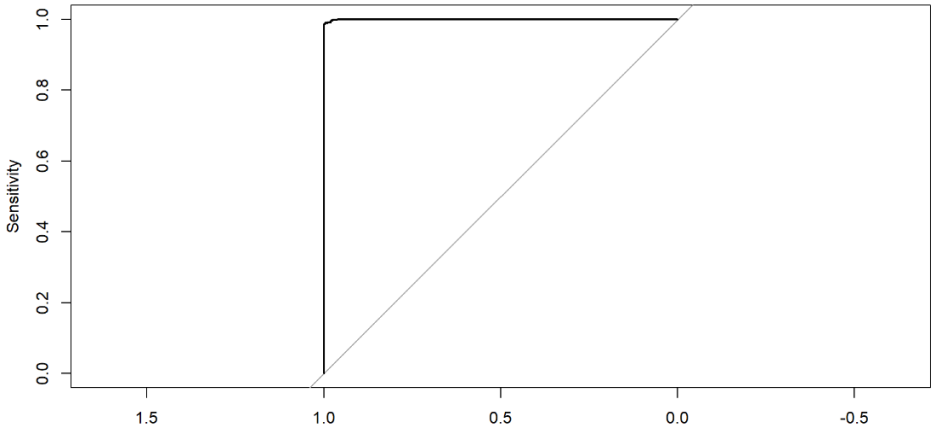


Figure 17 ROC Plot

Acc class

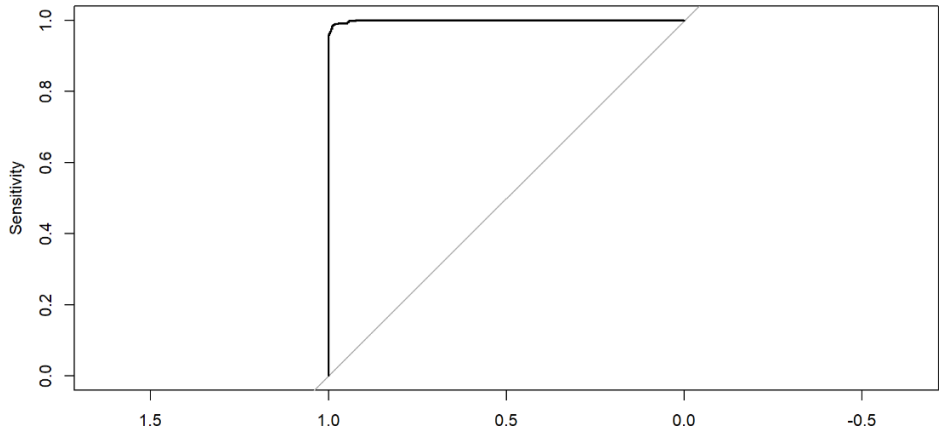


Figure 18 ROC Plot

Good class

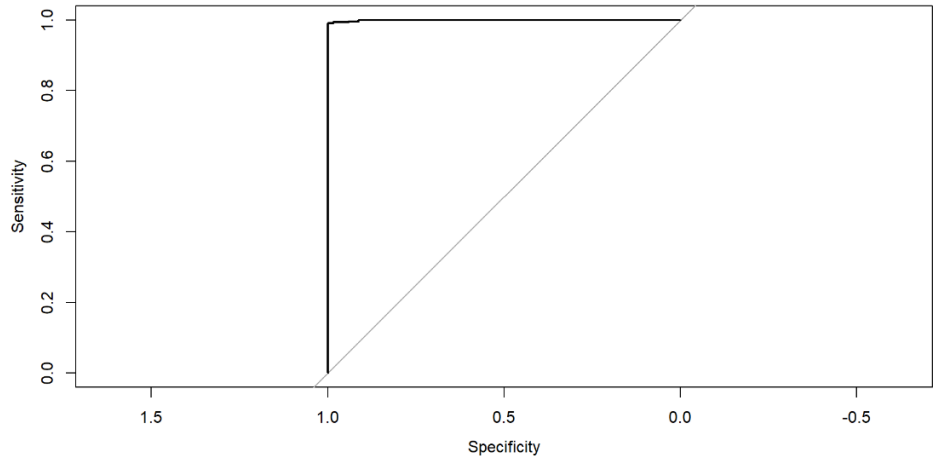


Figure 19 ROC Plot

Vgood class

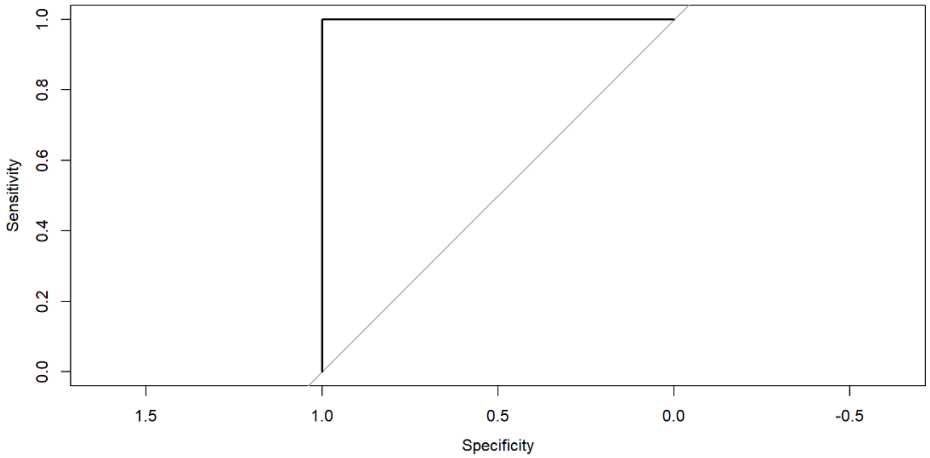


Figure 20 ROC Plot

Confusion Matrix and Statistics

```
Confusion Matrix and Statistics

          Reference
Prediction unacc  acc good vgood
     unacc  1198    5    0     0
     acc       9  371    1     1
     good      3    6   68     0
     vgood     0    2    0    64

Overall Statistics

               Accuracy : 0.9844
                 95% CI : (0.9773, 0.9897)
    No Information Rate : 0.7002
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.966

 Mcnemar's Test P-Value : NA
```

```
Statistics by Class:

                     Class: unacc Class: acc Class: good Class: vgood
Sensitivity                0.9901     0.9661     0.98551      0.98462
Specificity                0.9903     0.9918     0.99458      0.99880
Pos Pred Value             0.9958     0.9712     0.88312      0.96970
Neg Pred Value             0.9771     0.9903     0.99939      0.99940
Prevalence                 0.7002     0.2222     0.03993      0.03762
Detection Rate             0.6933     0.2147     0.03935      0.03704
Detection Prevalence       0.6962     0.2211     0.04456      0.03819
Balanced Accuracy          0.9902     0.9790     0.99004      0.99171
```

Plot of one tree from random forest

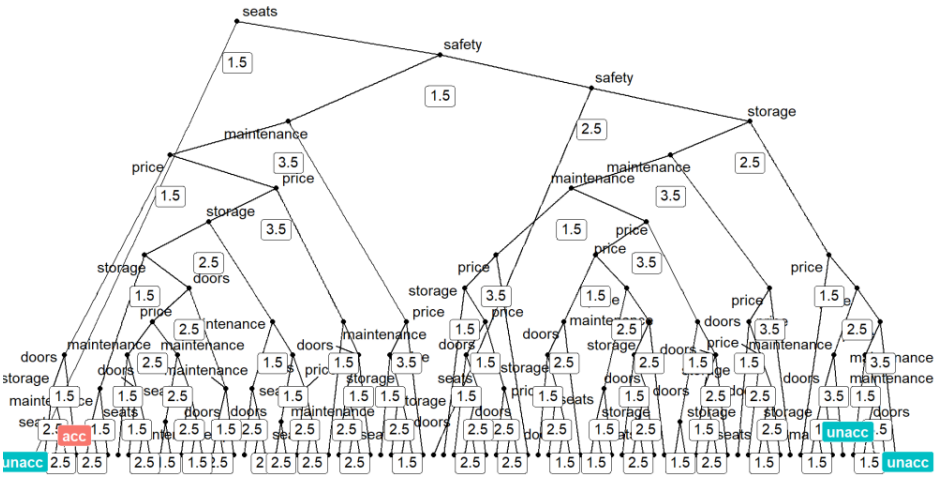


Figure 21 Sample Tree

AUC

```
> roc.multi$auc
Multi-class area under the curve: 1
```

Summary

Final model gave accuracy of 98.44% and AUC of 1 with parameters mtry=6, minsplit=10 and ntree=100.

Conclusion

The result analysis aligned with objective stated, optimized models are created for classification problem and have high accuracy (AUC for Decision Tree Analysis, Random Forest Analysis and Caret package are 0.8878, 0.9921, and 1 respectively). Model generated from Caret package shows the best predictive power. However, the accuracy of the models trends too high, which probability may not reflect the characteristics of the actual problem. It may cause by small data set resulting overfitting problem.

On the other hand, an interesting finding from Variable Importance Plots (Figure 9 & 16) is safety played the most important factor in customer making the purchase decision. The next important factors are price, maintenance and no of seats depending on the model referenced.

For next step actions, the first thing is to increase size of data set to refine the model. It is crucial to overcome the overfitting problem. Moreover, when time and resource are allowed more complex model like Neural Networks and Gradient Boosting can be test in future to see if any performance gain can be achieved.

Appendix

R Script

Decision Tree

```
library(rpart)

library(randomForest)

library(caret)

carData<-read.csv("D:/MSc CDA/Semester 2/3. Data and Text Mining_MCDA5580/Assignment 2/car.data")

head(carData)

trainIndex<-createDataPartition(carData$shouldBuy, p=0.8, list=FALSE)

train<-carData[trainIndex,]

test<-carData[-trainIndex,]


treeCar<-
rpart(shouldBuy~price+maintenance+doors+seats+storage+safety,data=train,method="class",control=rpart.control(minsplit=6))


#Plot Tree

plot(treeCar,uniform=TRUE,main="Decision Tree Should Buy")


text(treeCar,use.n=TRUE,all=TRUE,cex=.5,main="Decision Tree Should Buy")


plot(treeCar,uniform=TRUE,main="Decision Tree Should Buy")


# Plot Tree rules

rpart.rules(treeCar)


#Preduction

predCar<-predict(treeCar,newdata=test,type="class")
```

```
predCarProb<-predict(treeCar,newdata = test, type="prob")

head(predCar)
treeCarCM<-table(test[,"shouldBuy"],predCar)
treeCarCM
plot(predCar)

plot(treeCarCM)
sum(diag(treeCarCM)/sum(treeCarCM))

#Print Confusion Matrix & stat
test$shouldBuy <- factor(test$shouldBuy , levels=c("unacc", "acc", "good", "vgood"),
                         ordered=TRUE)
confusionMatrix(predCar, test[,"shouldBuy"])

#AUC
library(pROC)
roc.multi=multiclass.roc(test$shouldBuy, predCarProb[,2])
auc(roc.multi)

# Plot ROC
predictions<-as.data.frame(predict(treeCar, newdata = test, type = "prob"))
predictions$predict<-names(predictions)[1:4][apply(predictions[,1:4], 1, which.max)]
predictions$observed<-test$shouldBuy
head(predictions)
roc.unacc<-roc(ifelse(predictions$observed=="unacc", "unacc", "non-unacc"),
as.numeric(predictions$unacc))
roc.acc<-roc(ifelse(predictions$observed=="acc", "acc", "non-acc"), as.numeric(predictions$acc))
```

```
roc.good<-roc(ifelse(predictions$observed=="good", "good", "non-good"),
as.numeric(predictions$good))

roc.vgood<-roc(ifelse(predictions$observed=="vgood", "vgood", "non-vgood"),
as.numeric(predictions$vgood))

plot(roc.unacc,main="UNACC")

plot(roc.acc,main="ACC")

plot(roc.good,main="GOOD")

plot(roc.vgood,main="VGOOD")
```

Random Forest

```
library(rpart.plot)

library(caret)

library(randomForest)

library(pROC)


carData=read.csv('D:/#Spring 2023/5580 - Text Mining/Assignment2/car.csv',header = TRUE)


trainIndex <- createDataPartition(carData$shouldBuy, p = 0.8, list = FALSE)

train <- carData[trainIndex,]

test <- carData[-trainIndex,]



train$shouldBuy <- factor(train$shouldBuy , levels=c("unacc", "acc", "good", "vgood"),
                          ordered=TRUE)
test$shouldBuy <- factor(test$shouldBuy , levels=c("unacc", "acc", "good", "vgood"),
                          ordered=TRUE)


set.seed(123)
```

```
# Perform hyperparameter tuning

# 1. mtry

model <- tuneRF(train[,1:6], train[,7] , mtryStart = 2)


# 2. nodesize

# Try for the best value of node size


rf=randomForest(shouldBuy~price+maintenance+doors+seats+storage+safety,data=train, mtry =6,
nodesize= 1)


rfp <- predict(rf, newdata = test)

rfCM = table(rfp,test$shouldBuy)

rfProb =predict(rf, newdata = test,type="prob")

roc.multi <-multiclass.roc(test$shouldBuy, rfProb[,2])

rfCM

sum(diag(rfCM))/sum(rfCM)



rf=randomForest(shouldBuy~price+maintenance+doors+seats+storage+safety,data=train, mtry =6,
nodesize= 5)


rfp <- predict(rf, newdata = test)

rfCM = table(rfp,test$shouldBuy)

rfProb =predict(rf, newdata = test,type="prob")

roc.multi <-multiclass.roc(test$shouldBuy, rfProb[,2])

rfCM

sum(diag(rfCM))/sum(rfCM)
```

```
rf=randomForest(shouldBuy~price+maintenance+doors+seats+storage+safety,data=train, mtry =6,
nodesize= 10)

rfp <- predict(rf, newdata = test)

rfCM = table(rfp,test$shouldBuy)

rfProb =predict(rf, newdata = test,type="prob")

roc.multi <-multiclass.roc(test$shouldBuy, rfProb[,2])

rfCM

sum(diag(rfCM))/sum(rfCM)



# Build the optimized model

rf=randomForest(shouldBuy~price+maintenance+doors+seats+storage+safety,data=train, mtry =6,
nodesize= 1)

# Make predictions on the testing set

rfp <- predict(rf, newdata = test)

rfCM = table(rfp,test$shouldBuy)

rfProb=predict(rf, newdata = test,type="prob")

# plot ROC for different classes

predictions <- as.data.frame(predict(rf, newdata = test, type = "prob"))

predictions$predict <- names(predictions)[1:4][apply(predictions[,1:4], 1, which.max)]

predictions$observed <- test$shouldBuy

roc.unacc <- roc(ifelse(predictions$observed=="unacc", "unacc", "non-unacc"),
as.numeric(predictions$unacc))

roc.acc <- roc(ifelse(predictions$observed=="acc", "acc", "non-acc"), as.numeric(predictions$acc))
```

```
roc.good <- roc(ifelse(predictions$observed=="good", "good", "non-good"),
as.numeric(predictions$good))

roc.vgood <- roc(ifelse(predictions$observed=="vgood", "vgood", "non-vgood"),
as.numeric(predictions$vgood))


plot(roc.unacc)

plot(roc.acc)

plot(roc.good)

plot(roc.vgood)



#Print Confusion Matrix & stat

confusionMatrix(rfp, test$shouldBuy)


#Evaluate variable importance

importance(rf)

varImpPlot(rf)


#Print AUC

rfProb <- as.numeric(predict(rf, newdata = test, type = 'response'))

roc.multi <- multiclass.roc(test$shouldBuy, rfProb)

roc.multi$auc


#Plot of a Single Tree in the Random Forecast model


# Plot function

library(dplyr)

library(ggraph)

library(igraph)
```

```
tree_func <- function(final_model,
                      tree_num) {

  # get tree by index
  tree <- randomForest::getTree(final_model,
                                k = tree_num,
                                labelVar = TRUE) %>%
    tibble::rownames_to_column() %>%
    # make leaf split points to NA, so the 0s won't get plotted
    mutate(`split point` = ifelse(is.na(prediction), `split point`, NA))

  # prepare data frame for graph
  graph_frame <- data.frame(from = rep(tree$rowname, 2),
                            to = c(tree$`left daughter`, tree$`right daughter`))

  # convert to graph and delete the last node that we don't want to plot
  graph <- graph_from_data_frame(graph_frame) %>%
    delete_vertices("0")

  # set node labels
  V(graph)$node_label <- gsub("_", " ", as.character(tree$`split var`))
  V(graph)$leaf_label <- as.character(tree$prediction)
  V(graph)$split <- as.character(round(tree$`split point`, digits = 2))

  # plot
  plot <- ggraph(graph, 'dendrogram') +
    theme_bw() +
```

```
  geom_edge_link() +
  geom_node_point() +
  geom_node_text(aes(label = node_label), na.rm = TRUE, repel = TRUE) +
  geom_node_label(aes(label = split), vjust = 2.5, na.rm = TRUE, fill = "white") +
  geom_node_label(aes(label = leaf_label, fill = leaf_label), na.rm = TRUE,
                  repel = TRUE, colour = "white", fontface = "bold", show.legend = FALSE) +
  theme(panel.grid.minor = element_blank(),
        panel.grid.major = element_blank(),
        panel.background = element_blank(),
        plot.background = element_rect(fill = "white"),
        panel.border = element_blank(),
        axis.line = element_blank(),
        axis.text.x = element_blank(),
        axis.text.y = element_blank(),
        axis.ticks = element_blank(),
        axis.title.x = element_blank(),
        axis.title.y = element_blank(),
        plot.title = element_text(size = 18))

 print(plot)
}

# Plot tree
tree_func(final_model = rf, 1)
```

Caret Package

```
#rm(list = ls())    # Clear Environment
```

```
#cat("\014")       # Clear Console

library(randomForest)
library(caret)
library(pROC)
library(matrixStats)
library(Hmisc)



# Customized model over caret to add ntree, maxdepth and minsplit to grid search
# Reference https://rpubs.com/phamdinhkhanh/389752

customRF <- list(type = "Classification",
                 library = "randomForest",
                 loop = NULL)

customRF$parameters <- data.frame(parameter = c("mtry", "ntree", "maxdepth", "minsplit"),
                                  class = rep("numeric", 4),
                                  label = c("mtry", "ntree", "maxdepth", "minsplit"))

customRF$grid <- function(x, y, len = NULL, search = "grid") {}

customRF$fit <- function(x, y, wts, param, lev, last, weights, classProbs)
{
  randomForest(x, y,
               importance = TRUE,
               mtry = param$mtry,
               ntree=param$ntree,
```

```
        maxdepth=param$maxdepth,
        minsplit=param$minsplit)
}

#Predict label
customRF$predict <- function(modelFit, newdata, preProc = NULL, submodels = NULL)
  predict(modelFit, newdata)

#Predict prob
customRF$prob <- function(modelFit, newdata, preProc = NULL, submodels = NULL)
  predict(modelFit, newdata, type = "prob")

customRF$sort <- function(x) x[order(x[,1]),]
customRF$levels <- function(x) x$classes

# Main script starts here

carData=read.csv('car.csv',header = TRUE)

x=carData[,1:6]
y=carData[,7]

# Describe data

describe(x)
describe(y)

y <- factor(y, levels=c("unacc", "acc", "good", "vgood"),
```

```
        ordered=TRUE)

# Find Correlation between features

# Loop over all pairs of categorical variables

cols <- colnames(x)

for (i in 1:(length(cols) - 1))
{
  for (j in (i + 1):length(cols))
  {
    # Create a contingency table of the two categorical variables
    contingency_table <- table(x[, cols[i]], x[, cols[j]])
    print(paste('Contingency matrix of ', cols[i], ' vs ', cols[j]))
    print(contingency_table)
  }
}

# Modeling

set.seed(123)

# Training control for train-test split

control <- trainControl(method = "repeatedcv",
                        number = 5,
                        repeats = 3)
```

```
# Tuning grid search

tuning_grid <- expand.grid(mtry = c(3:6),
                           ntree = c(1, 5, 10, 100),
                           maxdepth = c(5),
                           minsplit = c(3, 5, 10))

# Model fitting and tuning search

rf_default <- train(x,y,
                    method=customRF,
                    tuneGrid=tuning_grid,
                    metric="Accuracy",
                    trControl=control)

# Print the model search results and final model

plot(rf_default)
print(rf_default$results)
print(rf_default)

# Importance plot

varImpPlot(rf_default$finalModel)

# Predict and print confusion matrix
```

```
predictions <- predict(rf_default$finalModel, data = x)
confusionMatrix(predictions,y)

#Print AUC
rfProb <- as.numeric(predict(rf_default$finalModel,
                             newdata = x, type = 'response'))
roc.multi <- multiclass.roc(y, rfProb)
roc.multi$auc

# Predict and print roc curve

predictions_prob <- predict(rf_default$finalModel,
                            data = x,
                            type = "prob")

predictions <- as.data.frame(predictions_prob)
predictions$predict <- names(predictions)[max.col(predictions[, 1:4], ties.method = "first")]
predictions$observed <- y
head(predictions)
roc.unacc <- roc(ifelse(predictions$observed=="unacc", "unacc", "non-unacc"),
as.numeric(predictions$unacc))
roc.acc <- roc(ifelse(predictions$observed=="acc", "acc", "non-acc"), as.numeric(predictions$acc))
roc.good <- roc(ifelse(predictions$observed=="good", "good", "non-good"),
as.numeric(predictions$good))
roc.vgood <- roc(ifelse(predictions$observed=="vgood", "vgood", "non-vgood"),
as.numeric(predictions$vgood))

plot(roc.unacc, title="Class uncc")
plot(roc.acc, title="Class acc")
```

```
plot(roc.good, title="Class good")
plot(roc.vgood, title="Class vgood")

#Plot of a Single Tree in the Random Forecast model
# Plot function
library(dplyr)
library(ggraph)
library(igraph)
tree_func <- function(final_model,tree_num)
 {
 # get tree by index
 tree <- randomForest::getTree(final_model,
                               k = tree_num,
                               labelVar = TRUE) %>%
  tibble::rownames_to_column() %>%
  # make leaf split points to NA, so the 0s won't get plotted
  mutate(`split point` = ifelse(is.na(prediction), `split point`, NA))
 # prepare data frame for graph
 graph_frame <- data.frame(from = rep(tree$rowname, 2),
                           to = c(tree$`left daughter`, tree$`right daughter`))
 # convert to graph and delete the last node that we don't want to plot
 graph <- graph_from_data_frame(graph_frame) %>%
  delete_vertices("0")
 # set node labels
 V(graph)$node_label <- gsub("_", " ", as.character(tree$`split var`))
 V(graph)$leaf_label <- as.character(tree$prediction)
 V(graph)$split <- as.character(round(tree$`split point`, digits = 2))
 # plot
```

```
  plot <- ggraph(graph, 'dendrogram') +
   theme_bw() +
   geom_edge_link() +
   geom_node_point() +
   geom_node_text(aes(label = node_label), na.rm = TRUE, repel = TRUE) +
   geom_node_label(aes(label = split), vjust = 2.5, na.rm = TRUE, fill = "white") +
   geom_node_label(aes(label = leaf_label, fill = leaf_label), na.rm = TRUE,
                   repel = TRUE, colour = "white", fontface = "bold", show.legend = FALSE) +
   theme(panel.grid.minor = element_blank(),
         panel.grid.major = element_blank(),
         panel.background = element_blank(),
         plot.background = element_rect(fill = "white"),
         panel.border = element_blank(),
         axis.line = element_blank(),
         axis.text.x = element_blank(),
         axis.text.y = element_blank(),
         axis.ticks = element_blank(),
         axis.title.x = element_blank(),
         axis.title.y = element_blank(),
         plot.title = element_text(size = 18))
  print(plot)
}
# Plot tree
tree_func(final_model = rf_default$finalModel, 1)
```

Reference/ Citation

Supervised Classification Model

https://emeritus.org/in/learn/types-of-supervised-learning/

https://machinelearningmastery.com/types-of-classification-in-machine-learning/

Random Forest Model

https://cran.r-project.org/web/packages/randomForest/randomForest.pdf

https://www.listendata.com/2014/11/random-forest-with-r.html#id-35df3b

Caret Package

https://www.machinelearningplus.com/machine-learning/caret-package/

The caret Package (topepo.github.io)

Random Forest Model tuning

https://afit-r.github.io/random_forests

Plot ROC Curve

https://stackoverflow.com/questions/46124424/how-can-i-draw-a-roc-curve-for-a-randomforest-model-with-three-classes-in-r

Plot tree in Random Forest

https://shiring.github.io/machine_learning/2017/03/16/rf_plot_ggraph

Customize Caret package for additional tuning parameter

https://rpubs.com/phamdinhkhanh/389752

Overfitting

https://crunchingthedata.com/random-forest-overfitting/