Predict activity quality from activity monitors

Abheer Shankar Prasad

23/10/2021

Introduction

Using devices such as Jawbone Up, Nike FuelBand, and Fitbit it is now possible to collect a large amount of data about personal activity relatively inexpensively. These type of devices are part of the quantified self movement – a group of enthusiasts who take measurements about themselves regularly to improve their health, to find patterns in their behavior, or because they are tech geeks. One thing that people regularly do is quantify how much of a particular activity they do, but they rarely quantify how well they do it.

In this project, we will use data from accelerometers on the belt, forearm, arm, and dumbell of 6 participants to predict the manner in which they did the exercise.

Data Preprocessing

```
library(lattice)
library(ggplot2)
library(caret)
library(kernlab)
```

```
##
## Attaching package: 'kernlab'
```

```
## The following object is masked from 'package:ggplot2':
##
##     alpha
```

```
library(rattle)
```

```
## Loading required package: tibble
```

```
## Loading required package: bitops
```

```
## Rattle: A free graphical interface for data science with R.
## Version 5.4.0 Copyright (c) 2006-2020 Togaware Pty Ltd.
## Type 'rattle()' to shake, rattle, and roll your data.
```

```
library(corrplot)
```

```
## corrplot 0.90 loaded
```

```
set.seed(1234)
```

Read the Data

After downloading the data from the data source, we can read the two csv files into two data frames.

```
traincsv <- read.csv("./data/pml-training.csv")
testcsv <- read.csv("./data/pml-testing.csv")

dim(traincsv)
```

```
## [1] 19622   160
```

```
dim(testcsv)
```

```
## [1]  20 160
```

The training data set contains 19622 observations and 160 variables, while the testing data set contains 20 observations and 160 variables. The “classe” variable in the training set is the outcome to predict.

Clean the data

Removing unnecessary variables. Starting with N/A variables.

```
traincsv <- traincsv[,colMeans(is.na(traincsv)) < .9] #removing mostly na columns
traincsv <- traincsv[,-c(1:7)]#removing metadata which is irrelevant to the outcome
```

Removing near zero variance variables.

```
nvz <- nearZeroVar(traincsv)
traincsv <- traincsv[,-nvz]
dim(traincsv)
```

```
## [1] 19622    53
```

Now that we have finished removing the unnecessary variables, we can now split the training set into a validation and sub training set. The testing set “testcsv” will be left alone, and used for the final quiz test cases.

```
inTrain <- createDataPartition(y=traincsv$classe, p=0.7, list=F)
train <- traincsv[inTrain,]
valid <- traincsv[-inTrain,]
```

Creating and Testing the Models

Here we will test a few popular models including: Decision Trees, Random Forest, Gradient Boosted Trees, and SVM. This is probably more than we will need to test, but just out of curiosity and good practice we will run them for comparison.

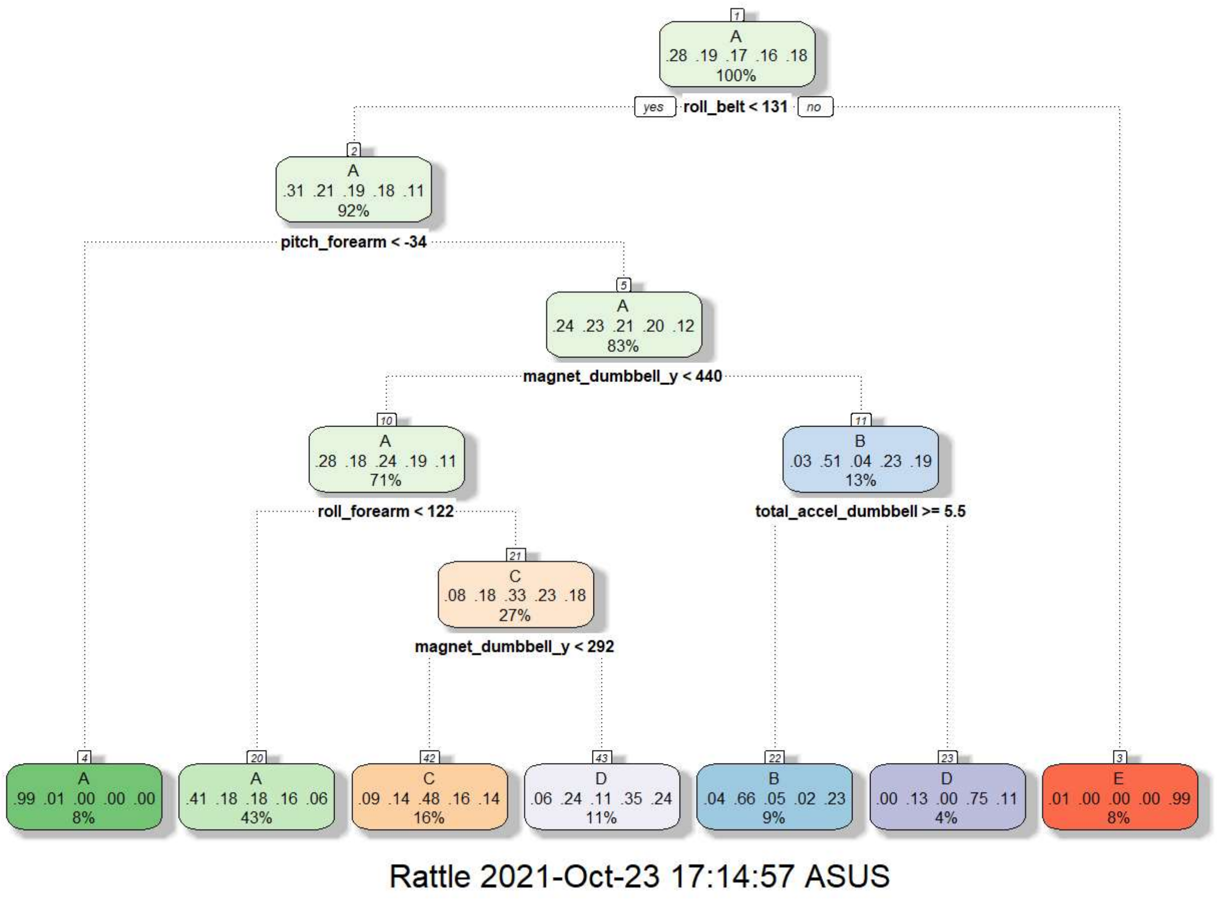
Set up control for training to use 3-fold cross validation.

```
control <- trainControl(method="cv", number=3, verboseIter=F)
```

Decision Tree

Model:

```
mod_trees <- train(classe~., data=train, method="rpart", trControl = control, tuneLength = 5)
fancyRpartPlot(mod_trees$finalModel)
```



Prediction:

```
pred_trees <- predict(mod_trees, valid)
cmtrees <- confusionMatrix(pred_trees, factor(valid$classe))
cmtrees
```

```
## Confusion Matrix and Statistics
## 
##           Reference
## Prediction    A    B    C    D    E
##          A 1519  473  484  451  156
##          B   28  355   45   10  130
##          C   83  117  423  131  131
##          D   40  194   74  372  176
##          E    4    0    0    0  489
## 
## Overall Statistics
##                                           
##                Accuracy : 0.5366          
##                  95% CI : (0.5238, 0.5494)
##     No Information Rate : 0.2845          
##     P-Value [Acc > NIR] : < 2.2e-16       
##                                           
##                   Kappa : 0.3957          
##                                           
##  Mcnemar's Test P-Value : < 2.2e-16       
## 
## Statistics by Class:
## 
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9074  0.31168  0.41228  0.38589  0.45194
## Specificity            0.6286  0.95512  0.90492  0.90165  0.99917
## Pos Pred Value         0.4927  0.62500  0.47797  0.43458  0.99189
## Neg Pred Value         0.9447  0.85255  0.87940  0.88228  0.89002
## Prevalence             0.2845  0.19354  0.17434  0.16381  0.18386
## Detection Rate         0.2581  0.06032  0.07188  0.06321  0.08309
## Detection Prevalence   0.5239  0.09652  0.15038  0.14545  0.08377
## Balanced Accuracy      0.7680  0.63340  0.65860  0.64377  0.72555
```

Random Forest

```
mod_rf <- train(classe~., data=train, method="rf", trControl = control, tuneLength = 5)

pred_rf <- predict(mod_rf, valid)
cmrf <- confusionMatrix(pred_rf, factor(valid$classe))
cmrf
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1673    4    0    0    0
##          B    1 1132    8    0    0
##          C    0    3 1016    5    1
##          D    0    0    2  958    0
##          E    0    0    0    1 1081
##
## Overall Statistics
##
##                Accuracy : 0.9958
##                  95% CI : (0.9937, 0.9972)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9946
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9994   0.9939   0.9903   0.9938   0.9991
## Specificity            0.9991   0.9981   0.9981   0.9996   0.9998
## Pos Pred Value         0.9976   0.9921   0.9912   0.9979   0.9991
## Neg Pred Value         0.9998   0.9985   0.9979   0.9988   0.9998
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2843   0.1924   0.1726   0.1628   0.1837
## Detection Prevalence   0.2850   0.1939   0.1742   0.1631   0.1839
## Balanced Accuracy      0.9992   0.9960   0.9942   0.9967   0.9994
```

Gradient Boosted Trees

```
mod_gbm <- train(classe~., data=train, method="gbm", trControl = control, tuneLength = 5, verbos
e = F)

pred_gbm <- predict(mod_gbm, valid)
cmgbm <- confusionMatrix(pred_gbm, factor(valid$classe))
cmgbm
```

```
## Confusion Matrix and Statistics
## 
##           Reference
## Prediction    A    B    C    D    E
##          A 1671    5    0    0    0
##          B    1 1128   15    0    0
##          C    2    6 1007    8    4
##          D    0    0    4  953    1
##          E    0    0    0    3 1077
## 
## Overall Statistics
## 
##                Accuracy : 0.9917
##                  95% CI : (0.989, 0.9938)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
## 
##                   Kappa : 0.9895
## 
##  Mcnemar's Test P-Value : NA
## 
## Statistics by Class:
## 
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9982   0.9903   0.9815   0.9886   0.9954
## Specificity            0.9988   0.9966   0.9959   0.9990   0.9994
## Pos Pred Value         0.9970   0.9860   0.9805   0.9948   0.9972
## Neg Pred Value         0.9993   0.9977   0.9961   0.9978   0.9990
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2839   0.1917   0.1711   0.1619   0.1830
## Detection Prevalence   0.2848   0.1944   0.1745   0.1628   0.1835
## Balanced Accuracy      0.9985   0.9935   0.9887   0.9938   0.9974
```

Support Vector Machine

```
mod_svm <- train(classe~., data=train, method="svmLinear", trControl = control, tuneLength = 5,
 verbose = F)

pred_svm <- predict(mod_svm, valid)
cmsvm <- confusionMatrix(pred_svm, factor(valid$classe))
cmsvm
```

```
## Confusion Matrix and Statistics
## 
##           Reference
## Prediction    A    B    C    D    E
##          A 1537  154   79   69   50
##          B   29  806   90   46  152
##          C   40   81  797  114   69
##          D   61   22   32  697   50
##          E    7   76   28   38  761
## 
## Overall Statistics
## 
##                Accuracy : 0.7813          
##                  95% CI : (0.7705, 0.7918)
##     No Information Rate : 0.2845          
##     P-Value [Acc > NIR] : < 2.2e-16       
## 
##                   Kappa : 0.722           
## 
##  Mcnemar's Test P-Value : < 2.2e-16       
## 
## Statistics by Class:
## 
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9182   0.7076   0.7768   0.7230   0.7033
## Specificity            0.9164   0.9332   0.9374   0.9665   0.9690
## Pos Pred Value         0.8137   0.7177   0.7239   0.8086   0.8363
## Neg Pred Value         0.9657   0.9301   0.9521   0.9468   0.9355
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2612   0.1370   0.1354   0.1184   0.1293
## Detection Prevalence   0.3210   0.1908   0.1871   0.1465   0.1546
## Balanced Accuracy      0.9173   0.8204   0.8571   0.8447   0.8362
```

Predicting on Test Data Set

Running our test set to predict the classe (5 levels) outcome for 20 cases with the Random Forest model.

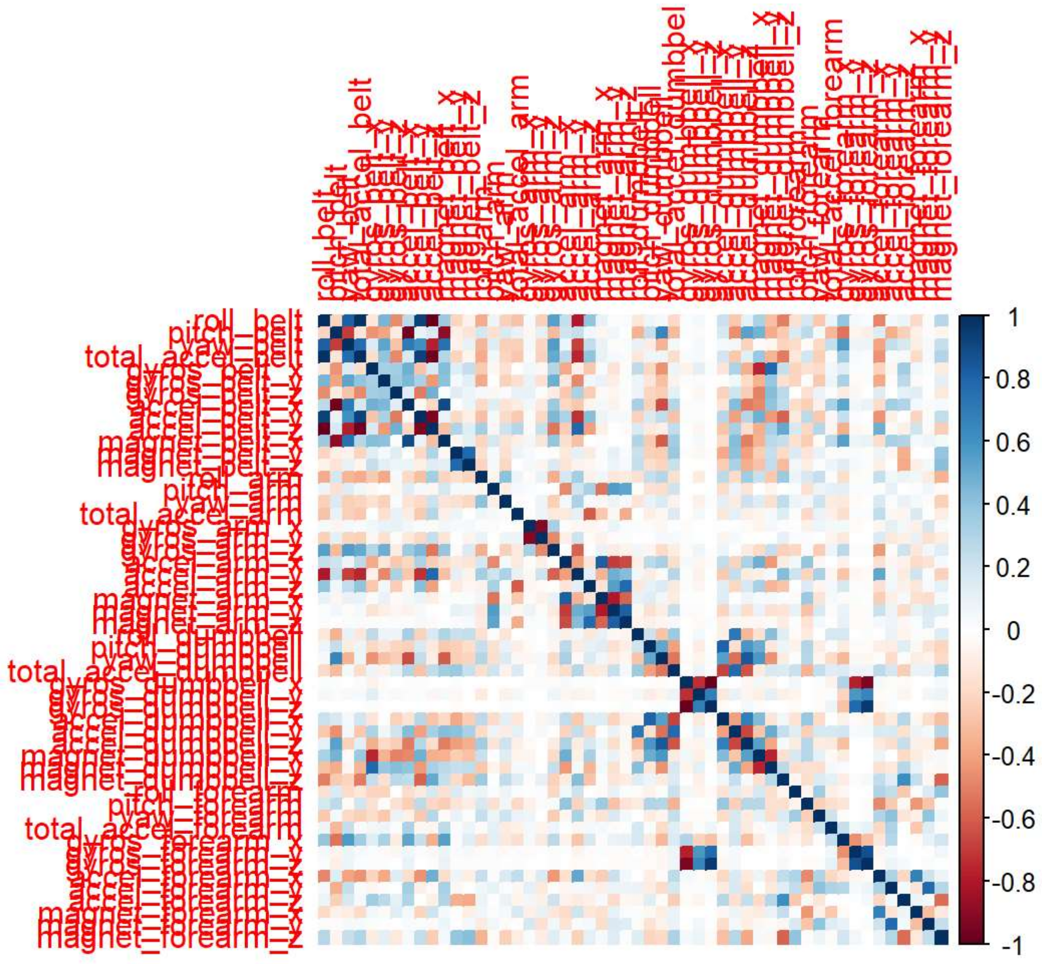
```
pred <- predict(mod_rf, testcsv)
print(pred)
```

```
##  [1] B A B A A E D B A A B C B A E E A B B B
## Levels: A B C D E
```

Appendix: Figures

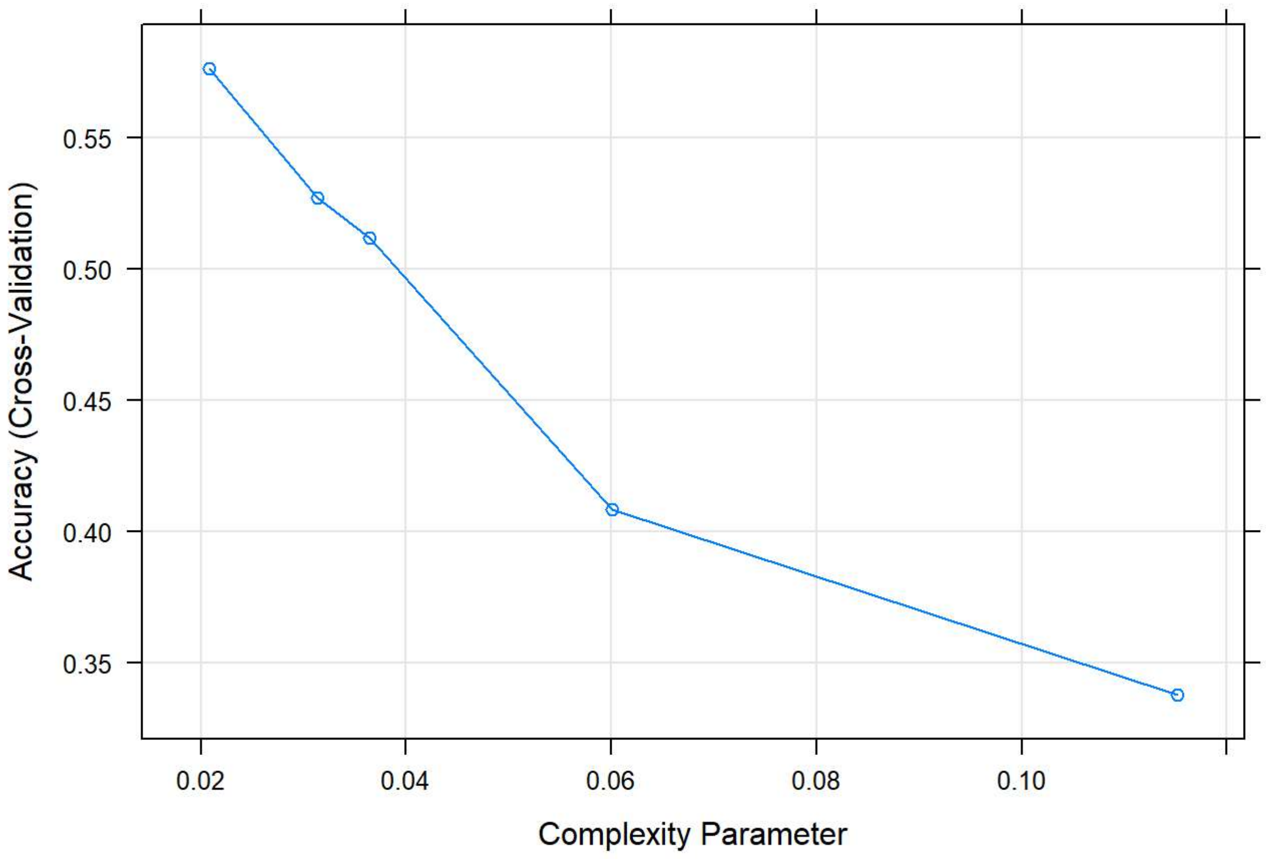
1.correlation matrix of variables in training set

```
corrPlot <- cor(train[, -length(names(train))])
corrplot(corrPlot, method="color")
```

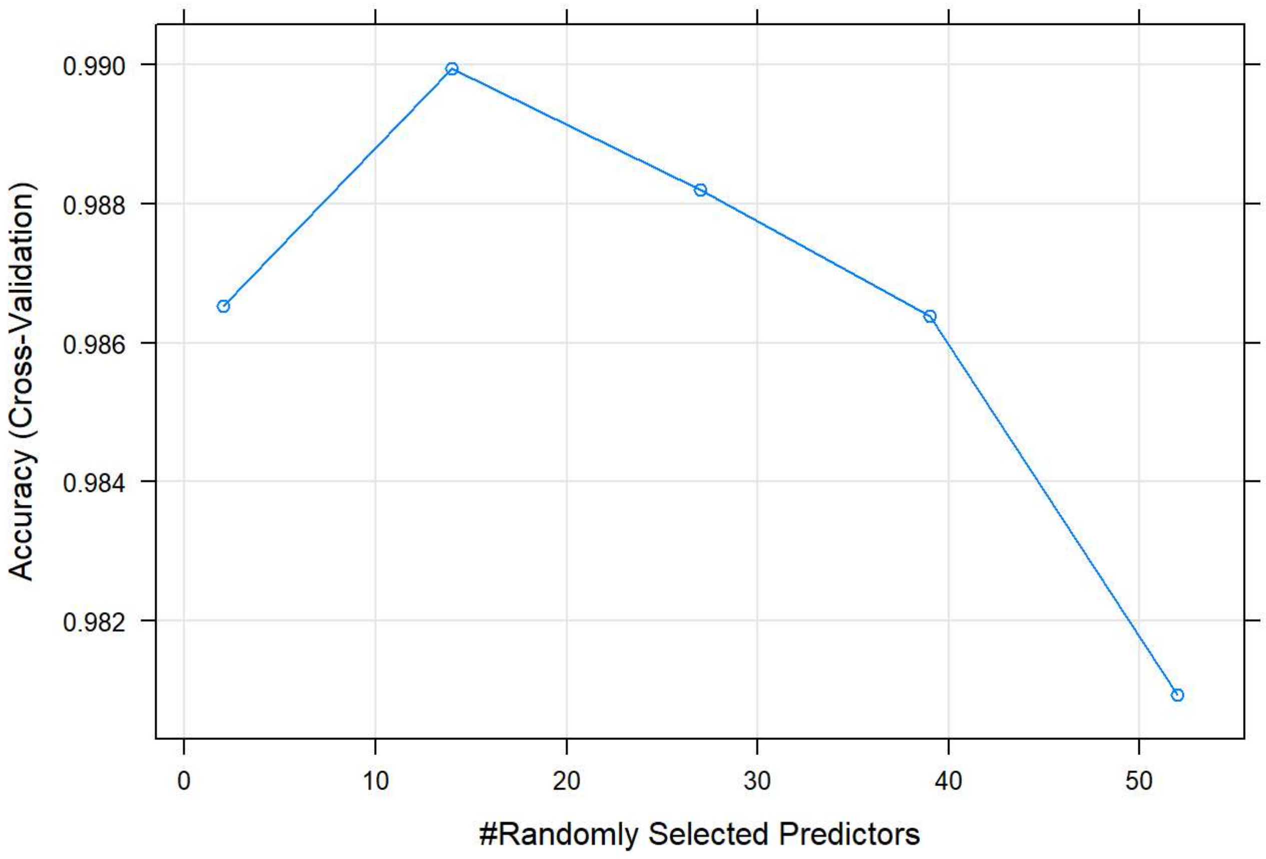


2.Plotting the models

```
plot(mod_trees)
```

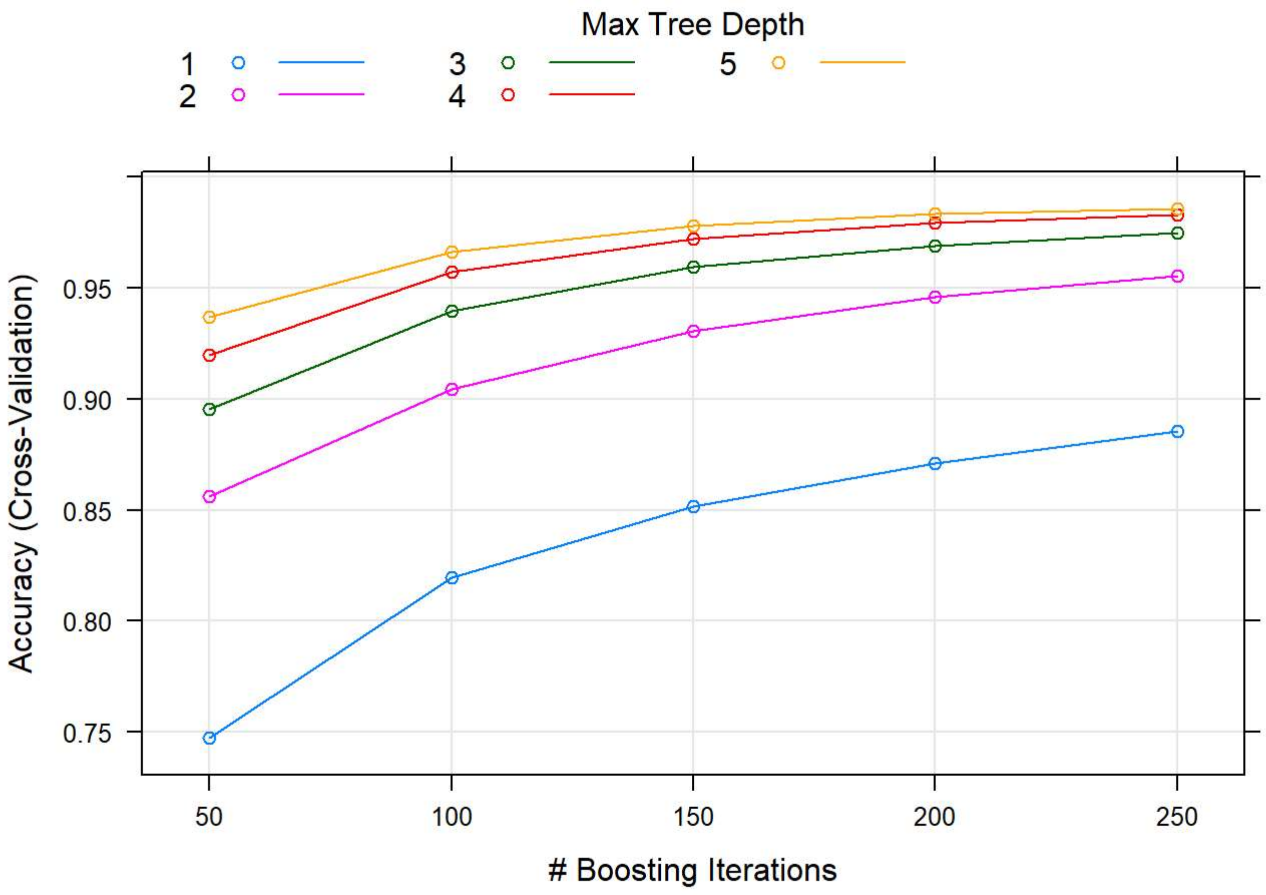

Accuracy (Cross-Validation)
0.55
0.50
0.45
0.40
0.35
0.02
0.04
0.06
0.08
0.10
Complexity Parameter

```
plot(mod_rf)
```



Accuracy (Cross-Validation)
0.990
0.988
0.986
0.984
0.982
0
10
20
30
40
50
#Randomly Selected Predictors

```
plot(mod_gbm)
```


Max Tree Depth
1
2
3
4
5
Accuracy (Cross-Validation)
0.75
0.80
0.85
0.90
0.95
50
100
150
200
250
# Boosting Iterations