Practical Machine Learning Project

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Overview

The goald of this project is to predict the manner in which they did the exercise.

Data

- The training data for this project are available here: https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv (https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv)
- The test data are available here: https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv (https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv)

Loading Data

Train set and Test Schema Verification

```
# Confirm both training set and test set contain identical variables
#  - excluding variable 'classe' from training set
#  - excluding variable 'problem_id' from test set

all.equal(colnames(raw_train)[1:(ncol(raw_train) - 1)],
          colnames(raw_test)[1:(ncol(raw_train) - 1)])
```

```
## [1] TRUE
```

Exploratory Data Analysis

Trainging data set

```
# trainging data

dim(raw_train)
```

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

```
# testing data
dim(raw_test)
```

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

```
# head(dt_train)
```

Prepare Environments

```
library(caret)
library(gbm)
library(randomForest)
library(rpart)
library(rpart.plot)
library(corrplot)
library(rattle)
library(RColorBrewer)
library(e1071)
set.seed(2019)
```

Data Cleaning and Tidying

1. Remove variables that contain any missing values.

```
dt_train <- raw_train[, colSums(is.na(raw_train)) == 0]
dt_test <- raw_test[, colSums(is.na(raw_test)) == 0]

# dimension of training set
dim(dt_train)
```

```
## [1] 19622    60
```

```
colnames(dt_train)
```

```
##  [1] "X"                    "user_name"            "raw_timestamp_part_1"
##  [4] "raw_timestamp_part_2" "cvtd_timestamp"       "new_window"
##  [7] "num_window"           "roll_belt"            "pitch_belt"
## [10] "yaw_belt"             "total_accel_belt"     "gyros_belt_x"
## [13] "gyros_belt_y"         "gyros_belt_z"         "accel_belt_x"
## [16] "accel_belt_y"         "accel_belt_z"         "magnet_belt_x"
## [19] "magnet_belt_y"        "magnet_belt_z"        "roll_arm"
## [22] "pitch_arm"            "yaw_arm"              "total_accel_arm"
## [25] "gyros_arm_x"          "gyros_arm_y"          "gyros_arm_z"
## [28] "accel_arm_x"          "accel_arm_y"          "accel_arm_z"
## [31] "magnet_arm_x"         "magnet_arm_y"         "magnet_arm_z"
## [34] "roll_dumbbell"        "pitch_dumbbell"       "yaw_dumbbell"
## [37] "total_accel_dumbbell" "gyros_dumbbell_x"     "gyros_dumbbell_y"
## [40] "gyros_dumbbell_z"     "accel_dumbbell_x"     "accel_dumbbell_y"
## [43] "accel_dumbbell_z"     "magnet_dumbbell_x"    "magnet_dumbbell_y"
## [46] "magnet_dumbbell_z"    "roll_forearm"         "pitch_forearm"
## [49] "yaw_forearm"          "total_accel_forearm"  "gyros_forearm_x"
## [52] "gyros_forearm_y"      "gyros_forearm_z"      "accel_forearm_x"
## [55] "accel_forearm_y"      "accel_forearm_z"      "magnet_forearm_x"
## [58] "magnet_forearm_y"     "magnet_forearm_z"     "classe"
```

```
# dimension of test set
dim(dt_test)
```

```
## [1] 20 60
```

```
colnames(dt_test)
```

```
##  [1] "X"                    "user_name"            "raw_timestamp_part_1"
##  [4] "raw_timestamp_part_2" "cvtd_timestamp"       "new_window"
##  [7] "num_window"           "roll_belt"            "pitch_belt"
## [10] "yaw_belt"             "total_accel_belt"     "gyros_belt_x"
## [13] "gyros_belt_y"         "gyros_belt_z"         "accel_belt_x"
## [16] "accel_belt_y"         "accel_belt_z"         "magnet_belt_x"
## [19] "magnet_belt_y"        "magnet_belt_z"        "roll_arm"
## [22] "pitch_arm"            "yaw_arm"              "total_accel_arm"
## [25] "gyros_arm_x"          "gyros_arm_y"          "gyros_arm_z"
## [28] "accel_arm_x"          "accel_arm_y"          "accel_arm_z"
## [31] "magnet_arm_x"         "magnet_arm_y"         "magnet_arm_z"
## [34] "roll_dumbbell"        "pitch_dumbbell"       "yaw_dumbbell"
## [37] "total_accel_dumbbell" "gyros_dumbbell_x"     "gyros_dumbbell_y"
## [40] "gyros_dumbbell_z"     "accel_dumbbell_x"     "accel_dumbbell_y"
## [43] "accel_dumbbell_z"     "magnet_dumbbell_x"    "magnet_dumbbell_y"
## [46] "magnet_dumbbell_z"    "roll_forearm"         "pitch_forearm"
## [49] "yaw_forearm"          "total_accel_forearm"  "gyros_forearm_x"
## [52] "gyros_forearm_y"      "gyros_forearm_z"      "accel_forearm_x"
## [55] "accel_forearm_y"      "accel_forearm_z"      "magnet_forearm_x"
## [58] "magnet_forearm_y"     "magnet_forearm_z"     "problem_id"
```

1. Remove identification variables which have no impacts on the prediction outcome: **classe**

```
dt_train <- dt_train[, -(1:5)]
dt_test <- dt_test[, -(1:5)]

# dimension of training set
dim(dt_train)
```

```
## [1] 19622    55
```

```
# dimension of test set
dim(dt_test)
```

```
## [1] 20 55
```

2. Remove variables which variance are near zero

```
near_zero <- nearZeroVar(dt_train)
dt_train <- dt_train[, -near_zero]

dim(dt_train)
```

```
## [1] 19622    54
```

Split training set for model training

Partition training set into 70% as train data for the modeling process, and 30% as test data for the model validation. The original test set remains unchanged.

```
model_train_split <- createDataPartition(dt_train$classe, p = 0.7, list = FALSE)
model_train = dt_train[model_train_split, ]
model_test = dt_train[-model_train_split, ]
```

```
dim(model_train)
```

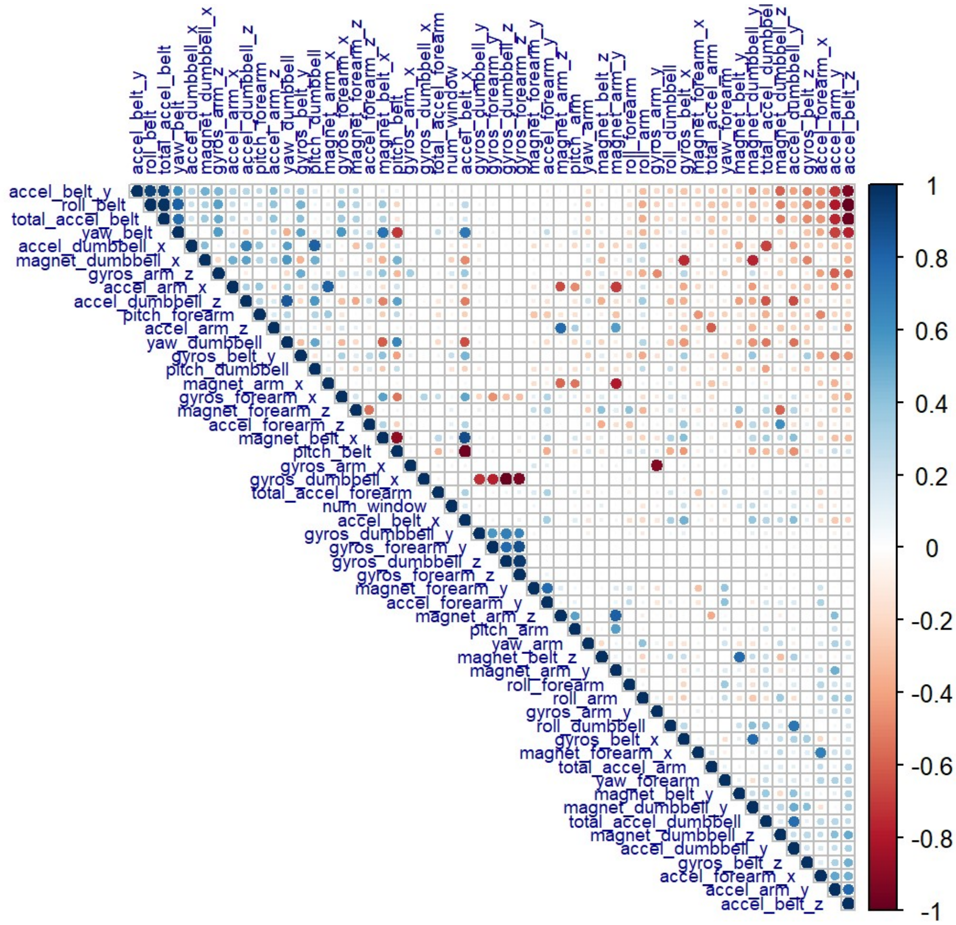
```
## [1] 13737    54
```

```
dim(model_test)
```

```
## [1] 5885   54
```

Variable Correlation Analysis

```
corr_matrix <- cor(model_train[, -54])
corrplot(corr_matrix,
         order="FPC", method = 'circle', type='upper',
         tl.cex = 0.6, tl.offset = 0.5, tl.col = 'darkblue')
```



The highly correlated variables are shown in dark circle in the figure above.

The names of highly correlated variables are

```
names(model_train)[findCorrelation(corr_matrix, cutoff = 0.75)]
```

```
##  [1] "accel_belt_z"      "roll_belt"         "accel_belt_y"
##  [4] "total_accel_belt"  "accel_dumbbell_z"  "accel_belt_x"
##  [7] "pitch_belt"        "magnet_dumbbell_x" "accel_dumbbell_y"
## [10] "magnet_dumbbell_y" "accel_dumbbell_x"  "accel_arm_x"
## [13] "accel_arm_z"       "magnet_arm_y"      "magnet_belt_z"
## [16] "accel_forearm_y"   "gyros_forearm_y"   "gyros_dumbbell_x"
## [19] "gyros_dumbbell_z"  "gyros_arm_x"
```

Prediction Model Building

To model the regressions, there are three commonly applied algorithms: 1. classification tree 2. Random Forest 3. Generalized Boosted Model

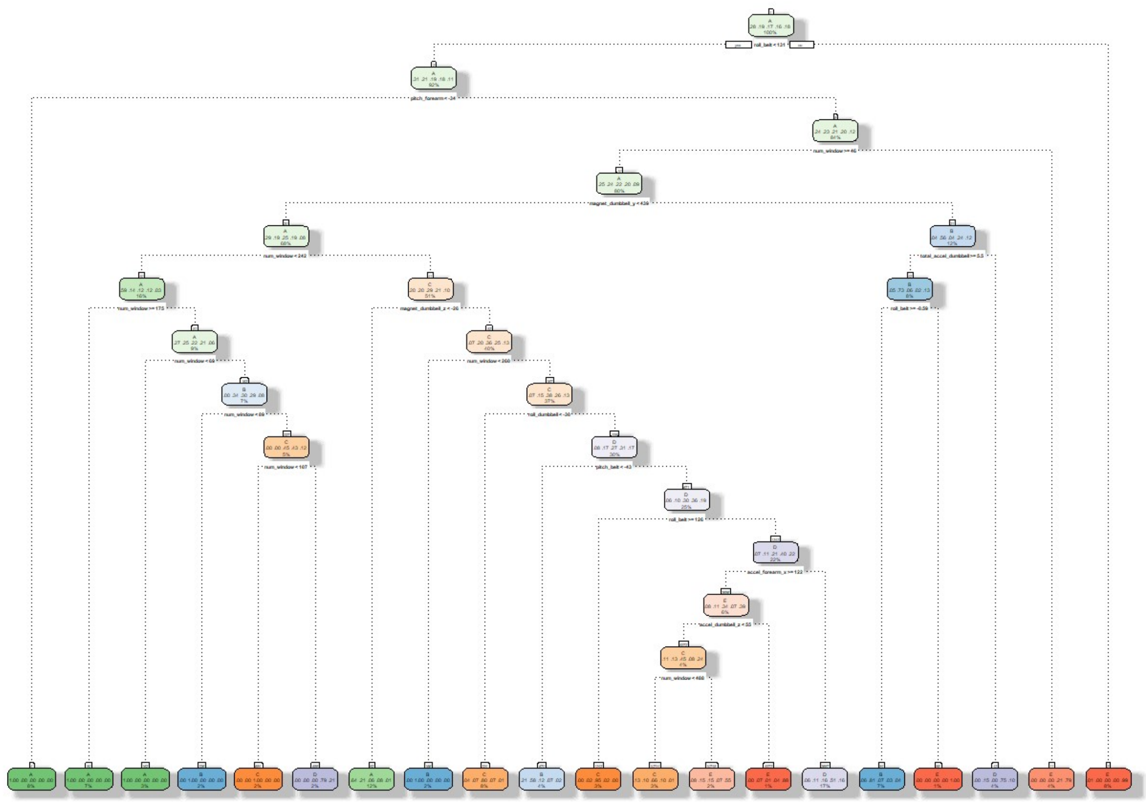
I will examine the performance of each algorithm and choose the best algorithm for this project.

Select Prediction Algorithm

1. Algorithm: Classification Tree

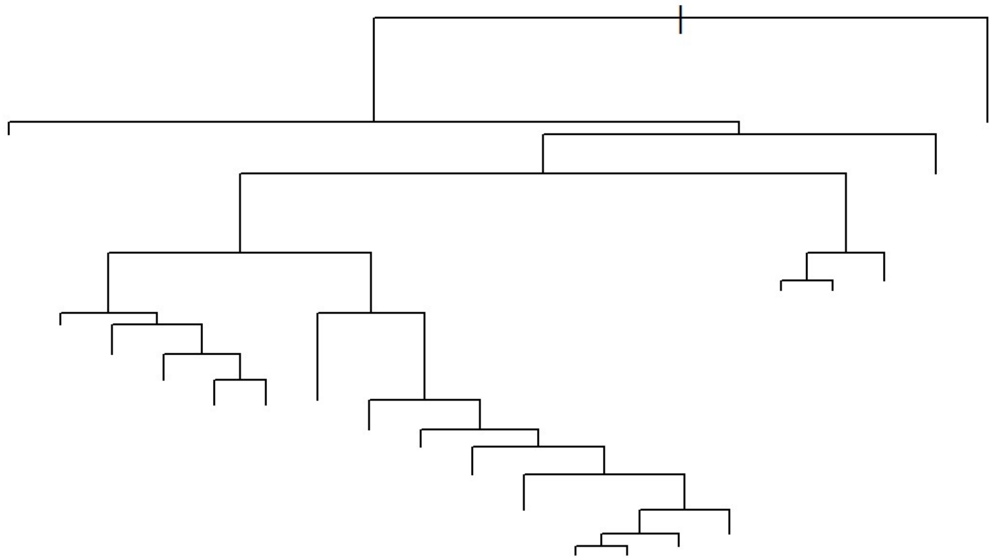
1. Train the model using classification tree

```
model_decisionTree <- rpart(classe ~., data = model_train, method = 'class')
fancyRpartPlot(model_decisionTree)
```



Rattle 2019-Mar-02 08:02:47 jtang

```
# plot the model
plot(model_decisionTree)
```



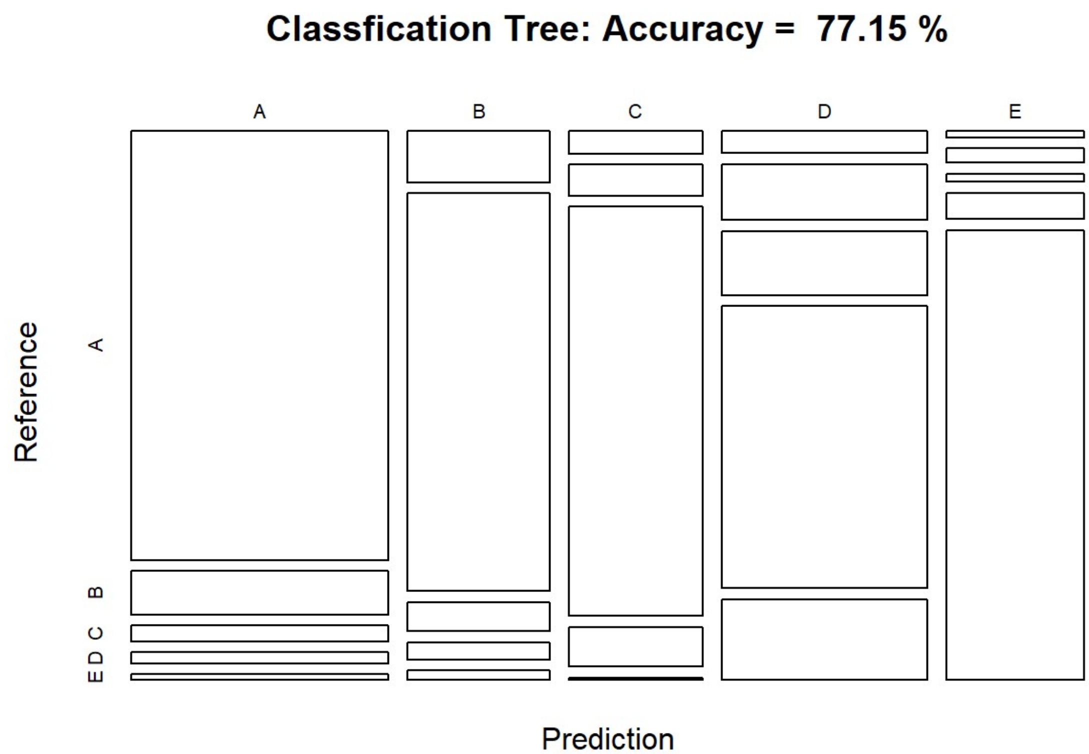
2. Validate the model

```
# prediction on test data
predict_decisionTree <- predict(model_decisionTree, model_test, type='class')
result_decisionTree <- confusionMatrix(predict_decisionTree, model_test$classe)
result_decisionTree
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1466  149   55   38   19
##          B   97  755   55   33   18
##          C   40   55  726   71    4
##          D   60  154  175  774  222
##          E   11   26   15   48  819
##
## Overall Statistics
##
##                Accuracy : 0.7715
##                  95% CI : (0.7605, 0.7821)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.7111
##  Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.8757   0.6629   0.7076   0.8029   0.7569
## Specificity            0.9380   0.9572   0.9650   0.8758   0.9792
## Pos Pred Value         0.8489   0.7881   0.8103   0.5588   0.8912
## Neg Pred Value         0.9500   0.9221   0.9399   0.9578   0.9470
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2491   0.1283   0.1234   0.1315   0.1392
## Detection Prevalence   0.2935   0.1628   0.1523   0.2353   0.1562
## Balanced Accuracy      0.9069   0.8100   0.8363   0.8394   0.8681
```

```
# plot the prediction result

plot(result_decisionTree$table,
     col = result_decisionTree$byClass,
     main = paste('Classfication Tree: Accuracy = ',
                  round(result_decisionTree$overall['Accuracy'],4) * 100,
                  '%'))
```



The accuracy of above model is 77.15% and its *out-of-sample error* is 22.85%.

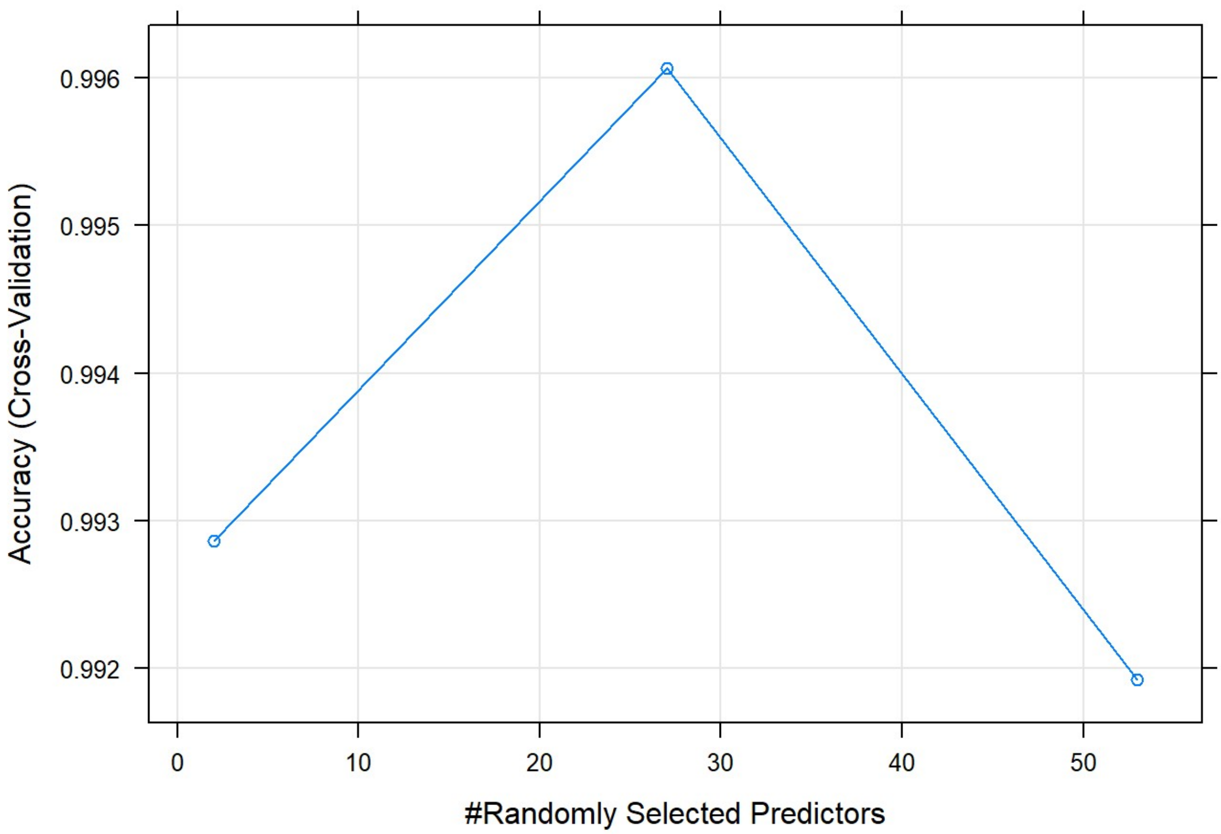
2. Algorithm: Random Forest

1. Train the model using Random Forest

```
model_randomForest <- train(classe ~.,
                            data = model_train,
                            method = 'rf',
                            trControl = trainControl(method="cv",
                                                     number=4,
                                                     verboseIter = FALSE))
model_randomForest$finalModel
```

```
##
## Call:
##  randomForest(x = x, y = y, mtry = param$mtry)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 27
##
##         OOB estimate of  error rate: 0.19%
## Confusion matrix:
##      A    B    C    D    E  class.error
## A 3905    0    0    0    1 0.0002560164
## B    6 2650    1    1    0 0.0030097818
## C    0    4 2392    0    0 0.0016694491
## D    0    0    7 2244    1 0.0035523979
## E    0    1    0    4 2520 0.0019801980
```

```
# plot the model
plot(model_randomForest)
```



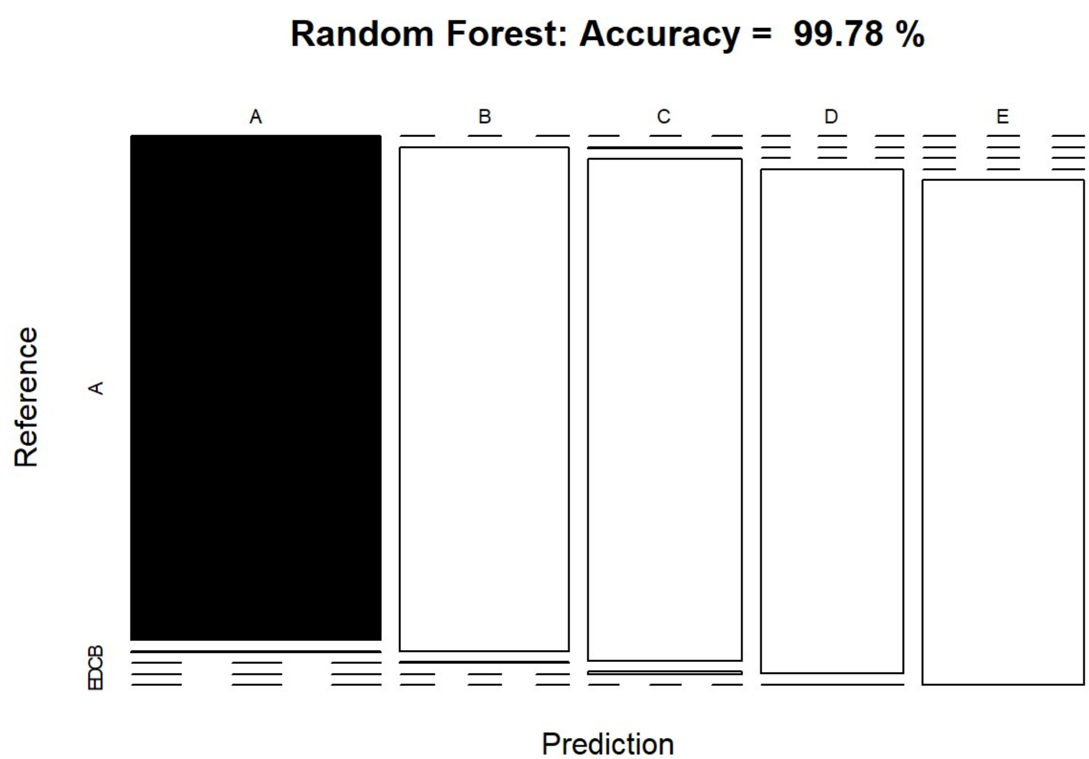
2. Validate the model

```r
# prediction on test data
predict_randomForest <- predict(model_randomForest, model_test)
result_randomForest <- confusionMatrix(predict_randomForest, model_test$classe)
result_randomForest
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1674    3    0    0    0
##          B    0 1134    2    0    0
##          C    0    2 1024    5    0
##          D    0    0    0  959    1
##          E    0    0    0    0 1081
##
## Overall Statistics
##
##                Accuracy : 0.9978
##                  95% CI : (0.9962, 0.9988)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9972
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   0.9956   0.9981   0.9948   0.9991
## Specificity            0.9993   0.9996   0.9986   0.9998   1.0000
## Pos Pred Value         0.9982   0.9982   0.9932   0.9990   1.0000
## Neg Pred Value         1.0000   0.9989   0.9996   0.9990   0.9998
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2845   0.1927   0.1740   0.1630   0.1837
## Detection Prevalence   0.2850   0.1930   0.1752   0.1631   0.1837
## Balanced Accuracy      0.9996   0.9976   0.9983   0.9973   0.9995
```

```r
# plot the prediction result

plot(result_randomForest$table,
     col = result_randomForest$byClass,
     main = paste('Random Forest: Accuracy = ',
                  round(result_randomForest$overall['Accuracy'],4) * 100,
                  '%'))
```



The accuracy of above model is 99.78% and its out-of-sample error is only 0.22% which is every good.

3. Algorithm: Generalized Boosted Model

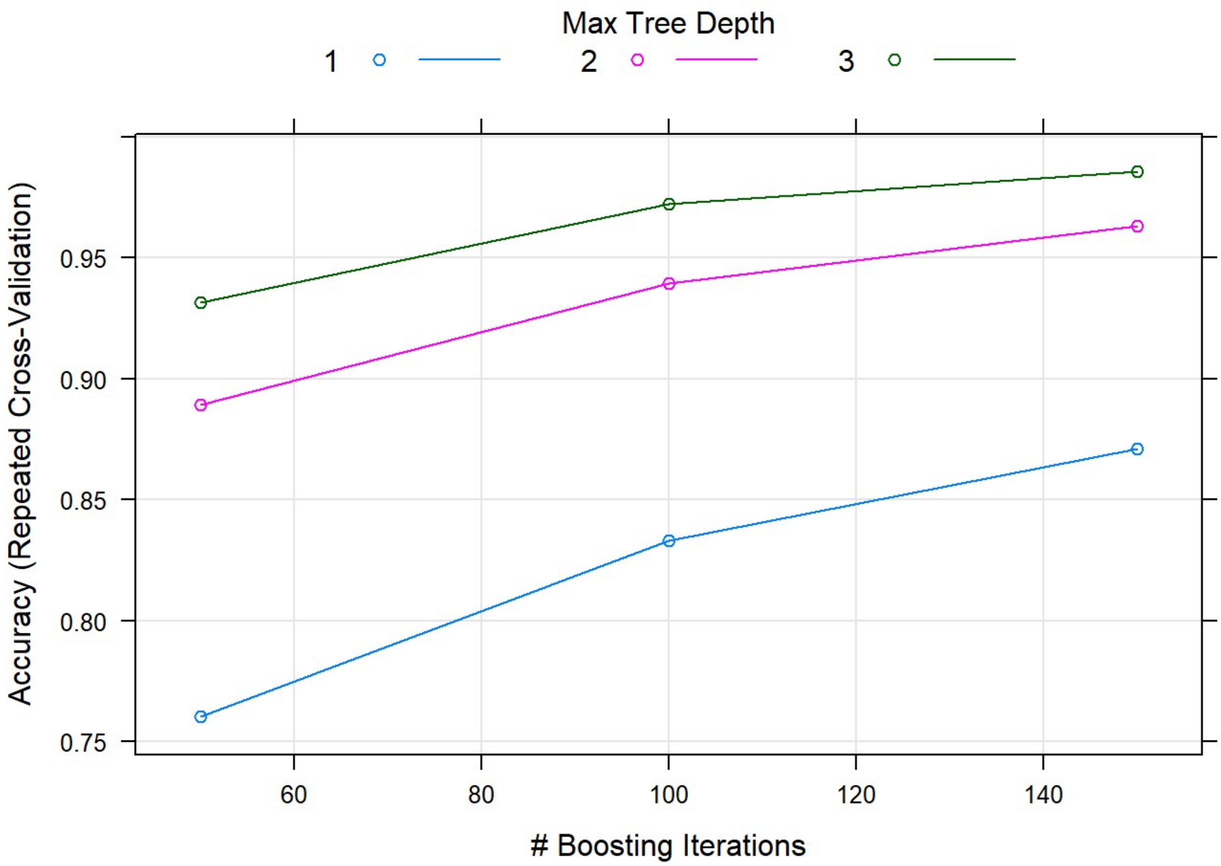
1. Train the model using Generalized Boosted Model

```
model_GBM <- train(classe ~.,
                    data = model_train,
                    method = 'gbm',
                    trControl = trainControl(method="repeatedcv",
                                             number= 5,
                                             repeats = 1,
                                             verboseIter = FALSE),
                   verbose = FALSE)

model_GBM$finalModel
```

```
## A gradient boosted model with multinomial loss function.
## 150 iterations were performed.
## There were 53 predictors of which 53 had non-zero influence.
```

```
# plot the model
plot(model_GBM)
```



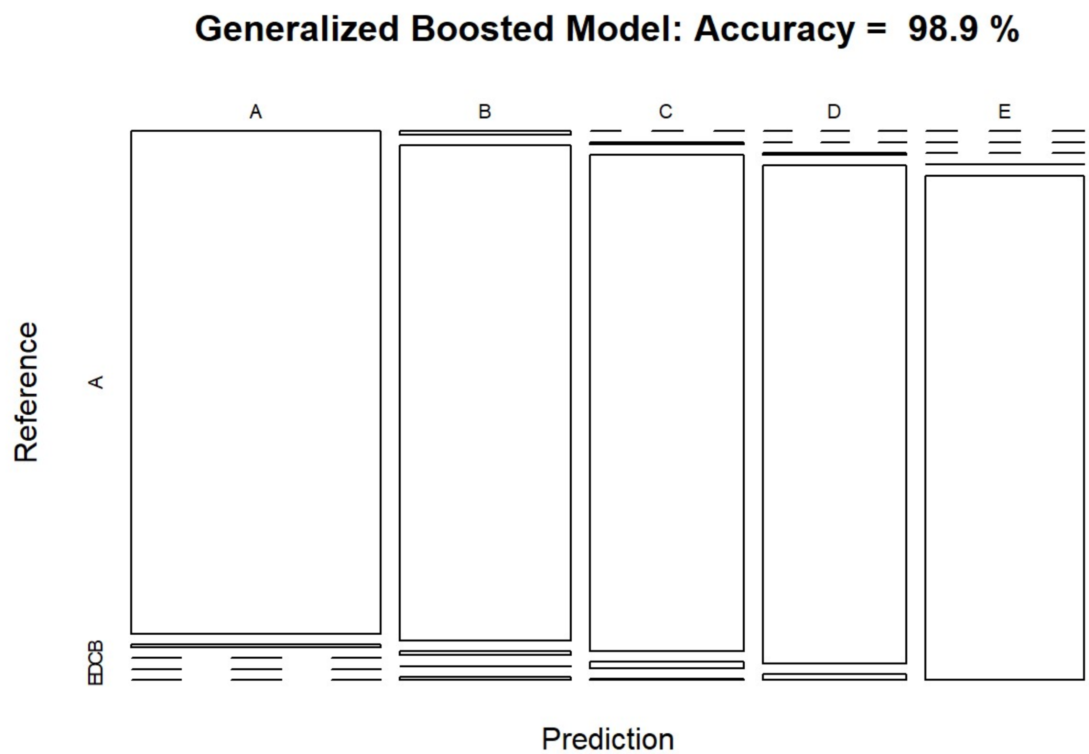
2. Validate the model

```
# prediction on test data
predict_GBM <- predict(model_GBM, model_test)
result_GBM <- confusionMatrix(predict_GBM, model_test$classe)
result_GBM
```

```
## Confusion Matrix and Statistics
## 
##           Reference
## Prediction    A    B    C    D    E
##          A 1666    8    0    0    0
##          B    8 1127    8    1    6
##          C    0    4 1015   13    2
##          D    0    0    3  949   11
##          E    0    0    0    1 1063
## 
## Overall Statistics
## 
##                Accuracy : 0.989
##                  95% CI : (0.9859, 0.9915)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
## 
##                   Kappa : 0.986
##  Mcnemar's Test P-Value : NA
## 
## Statistics by Class:
## 
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9952   0.9895   0.9893   0.9844   0.9824
## Specificity            0.9981   0.9952   0.9961   0.9972   0.9998
## Pos Pred Value         0.9952   0.9800   0.9816   0.9855   0.9991
## Neg Pred Value         0.9981   0.9975   0.9977   0.9970   0.9961
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2831   0.1915   0.1725   0.1613   0.1806
## Detection Prevalence   0.2845   0.1954   0.1757   0.1636   0.1808
## Balanced Accuracy      0.9967   0.9923   0.9927   0.9908   0.9911
```

```
# plot the prediction result

plot(result_GBM$table,
     col = result_GBM$byClass,
     main = paste('Generalized Boosted Model: Accuracy = ',
                  round(result_GBM$overall['Accuracy'],4) * 100,
                  '%'))
```



The accuracy of above model is 98.90% and its out-of-sample error is only 1.10% which is also good.

Concludsion of Model Selection

The accuracy of above 3 regression modeling algorithm are:

1. Classification Tree: 77.15%
2. Random Forest: 99.78%
3. Generalized Boosted Model: 98.90%

As Random Forest produce the highest accuracy among the 3 algorithms. I will apply it to predict the result from test dataset.

Predict the result

```
predict_final <- predict(model_randomForest, dt_test)
predict_final
```

```
##  [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
```