Including Plot

Prediction Assignment Write up

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Overview

This analysis meant to be the basis for the course quiz and a prediction assignment write up. The main goal of the project is to predict the manner in which 6 participants performed some exercise as described below. This is the “class” variable in the training set. The machine learning algorithm described here is applied to the 20 test cases available in the test data and the predictions are submitted in appropriate format to the Course Project Prediction Quiz for automated grading.

Data Loading and Exploratory Analysis

Data Source

The training data for this project are available here:

[Training Set] https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv

The test data are available here:

[Test Set] https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv

Environment Setup

```
library(knitr)
library(caret)
library(rpart)
library(rpart.plot)
library(rattle)
library(randomForest)
library(corrplot)

set.seed(301)
```

Data Loading and Cleaning

The next step is loading the dataset from the URL provided above. The training dataset is then partitioned in 2 to create a Training set (70% of the data) for the modeling process and a Test set (with the remaining 30%) for the validations. The testing dataset is not changed and will only be used for the quiz results generation.

```
TrainUrl <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"

TestUrl <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"

TrainFile<-"pml-traininig.csv"

TestFile<-"pml-testing.csv"
```

Download the datasets

```
if(!file.exists(TrainFile)) {
  download.file(TrainUrl,destfile = TrainFile)
  }
training <- read.csv(TrainFile)
if(!file.exists(TestFile)) {
  download.file(TestUrl,destfile = TestFile)
  }
testing <- read.csv(TestFile)
```

Create a partition using caret with the training dataset on 70,30 ratio

```
inTrain <- createDataPartition(training$classe, p=0.7, list=FALSE)

TrainSet <- training[inTrain, ]

TestSet <- training[-inTrain, ]

dim(TrainSet)
```

```
## [1] 13737   160
```

```
dim(TestSet)
```

```
## [1] 5885  160
```

Both created datasets have 160 variables. Let’s clean NA, The Near Zero variance (NZV) variables and the ID variables as well.

Remove variables with Nearly Zero Variance

```
NZV <- nearZeroVar(TrainSet)
TrainSet <- TrainSet[, -NZV]
TestSet <- TestSet[, -NZV]
dim(TestSet)
```

```
## [1] 5885  105
```

```
dim(TrainSet)
```

```
## [1] 13737   105
```

Remove variables that are mostly NA

```
AllNA <- sapply(TrainSet, function(x) mean(is.na(x))) > 0.95
TrainSet <- TrainSet[, AllNA==FALSE]
TestSet <- TestSet[, AllNA==FALSE]
dim(TestSet)
```

```
## [1] 5885   59
```

```
dim(TrainSet)
```

```
## [1] 13737    59
```

Remove identification only variables (columns 1 to 5)

```
TrainSet <- TrainSet[, -(1:5)]
TestSet <- TestSet[, -(1:5)]
dim(TrainSet)
```

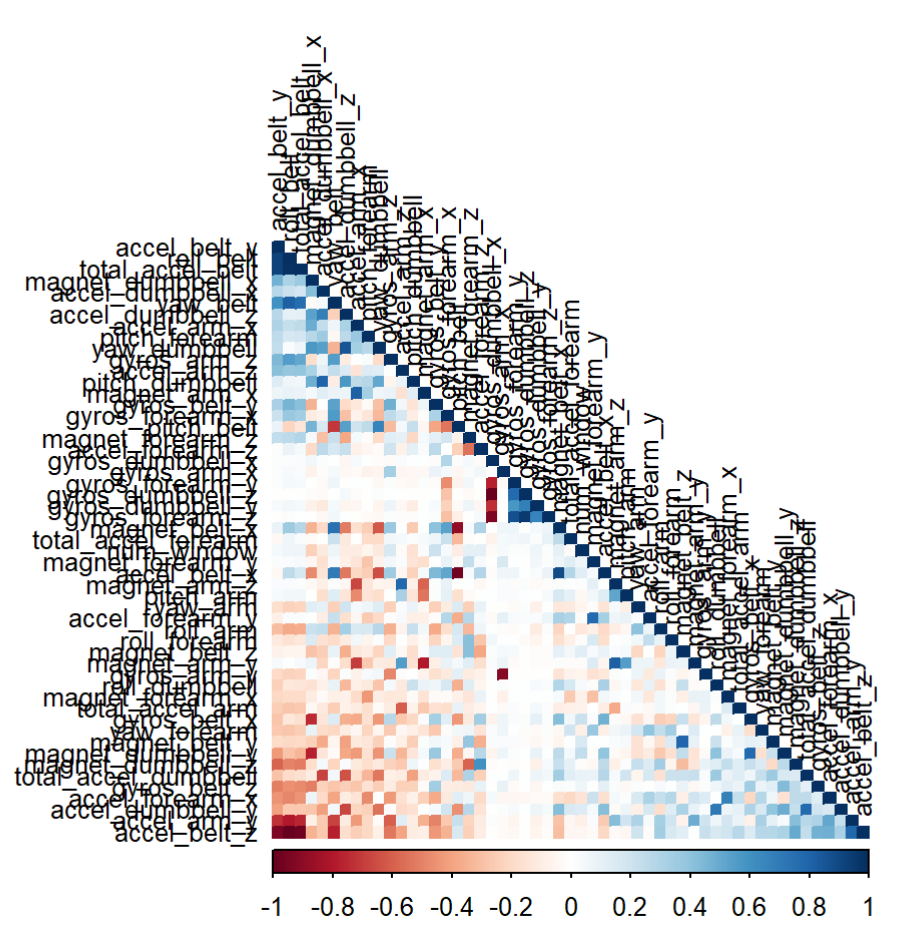
```
## [1] 13737    54
```

After cleaning, we can see that the number of variables for the analysis are now only 53.

Correlation Analysis

A correlation among variables is analysed before proceeding to the modeling procedures.

```
corMatrix <- cor(TrainSet[, -54])
corrplot(corMatrix, order = "FPC", method = "color", type = "lower", tl.cex = 0.8, tl.col = rgb(0, 0, 0))
```



The highly correlated variables are shown in dark colors in the graph above. To make an even more compact analysis, a PCA (Principal Components Analysis) could be performed as pre-processing step to the datasets. Nevertheless, as the correlations are quite few, this step will not be applied for this assignment.

Prediction Model Building

Three popular methods will be applied to model the regressions (in the Train dataset) and the best one (with higher accuracy when applied to the Test dataset) will be used for the quiz predictions. The methods are: Random Forests, Decision Tree and Generalized Boosted Model, as described below. A Confusion Matrix is plotted at the end of each analysis to better visualize the accuracy of the models.

Random Forests

Model fit

```
set.seed(301)
controlRF <- trainControl(method="cv", number=3, verboseIter=FALSE)
modFitRandForest <- train(classe ~ ., data=TrainSet, method="rf", trContro =controlRF)
modFitRandForest$finalModel
```

```
##
## Call:
##  randomForest(x = x, y = y, mtry = min(param$mtry, ncol(x)), trContro = ..1)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 27
##
##         OOB estimate of  error rate: 0.23%
## Confusion matrix:
##      A    B    C    D    E  class.error
## A 3904    2    0    0    0 0.0005120328
## B    6 2648    3    1    0 0.0037622272
## C    0    4 2392    0    0 0.0016694491
## D    0    0    8 2243    1 0.0039964476
## E    0    1    0    5 2519 0.0023762376
```

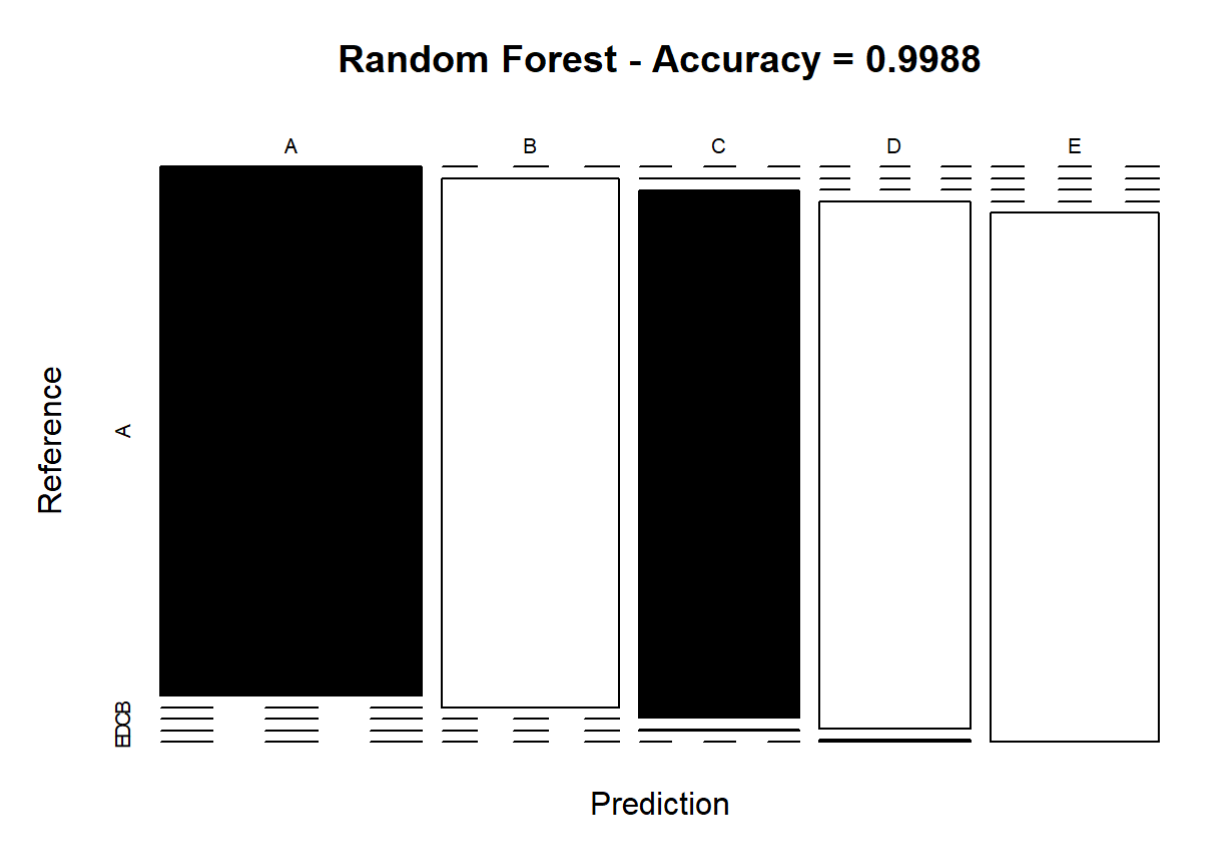
Prediction on Test dataset

```
predictRandForest <- predict(modFitRandForest, newdata=TestSet)
confMatRandForest <- confusionMatrix(predictRandForest, as.factor(TestSet$classe))
confMatRandForest
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1674    0    0    0    0
##          B    0 1138    0    0    0
##          C    0    1 1026    2    0
##          D    0    0    0  962    4
##          E    0    0    0    0 1078
##
## Overall Statistics
##
##                Accuracy : 0.9988
##                  95% CI : (0.9976, 0.9995)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9985
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   0.9991   1.0000   0.9979   0.9963
## Specificity            1.0000   1.0000   0.9994   0.9992   1.0000
## Pos Pred Value         1.0000   1.0000   0.9971   0.9959   1.0000
## Neg Pred Value         1.0000   0.9998   1.0000   0.9996   0.9992
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2845   0.1934   0.1743   0.1635   0.1832
## Detection Prevalence   0.2845   0.1934   0.1749   0.1641   0.1832
## Balanced Accuracy      1.0000   0.9996   0.9997   0.9986   0.9982
```

Plot matrix results

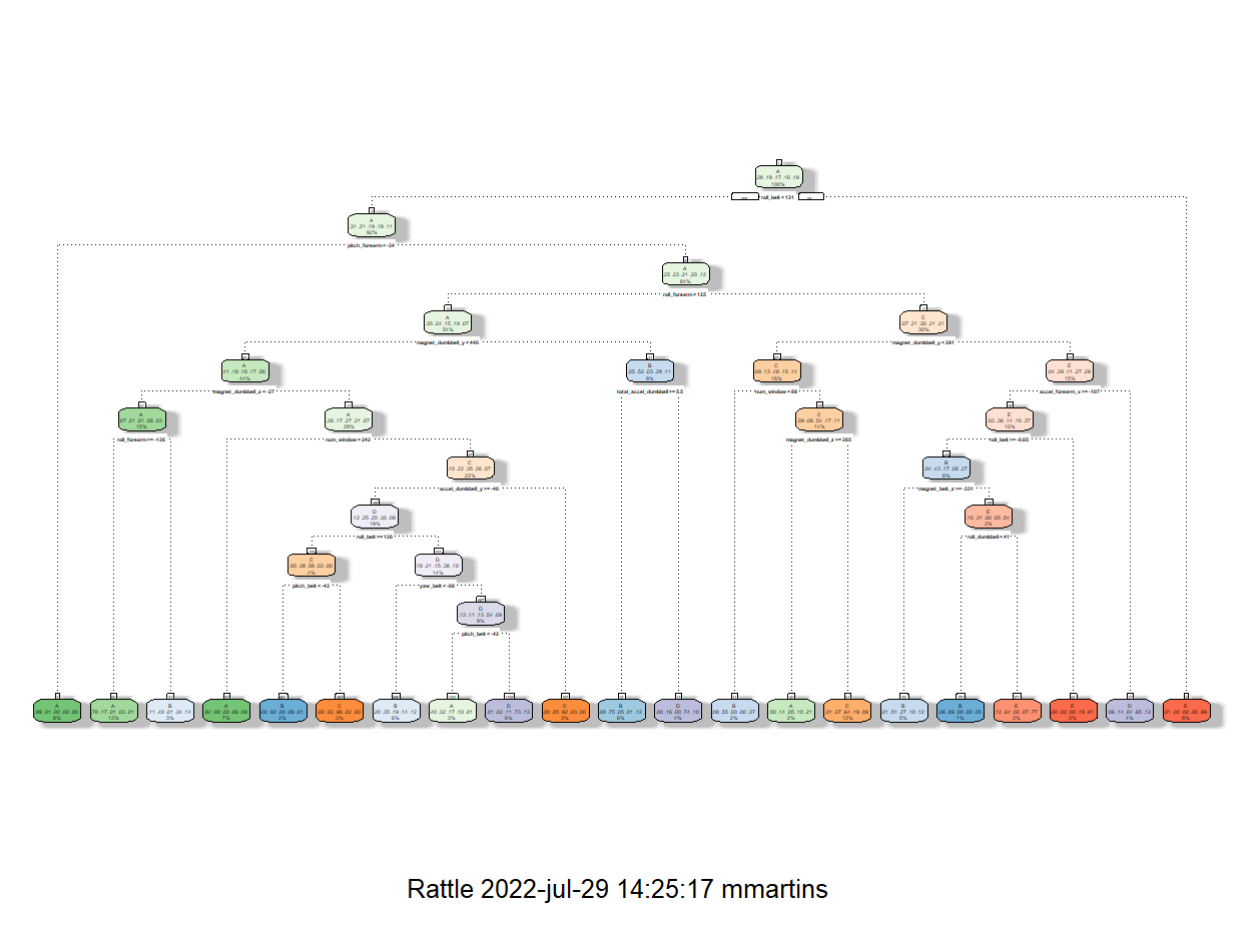
```
plot(confMatRandForest$table, col = confMatRandForest$byClass, main = paste("Random Forest - Accuracy =", round(c
onfMatRandForest$overall['Accuracy'], 4)))
```



Decision Tree

Model fit

```
set.seed(301)
modFitDecTree <- rpart(classe ~ ., data=TrainSet, method="class")
fancyRpartPlot(modFitDecTree)
```



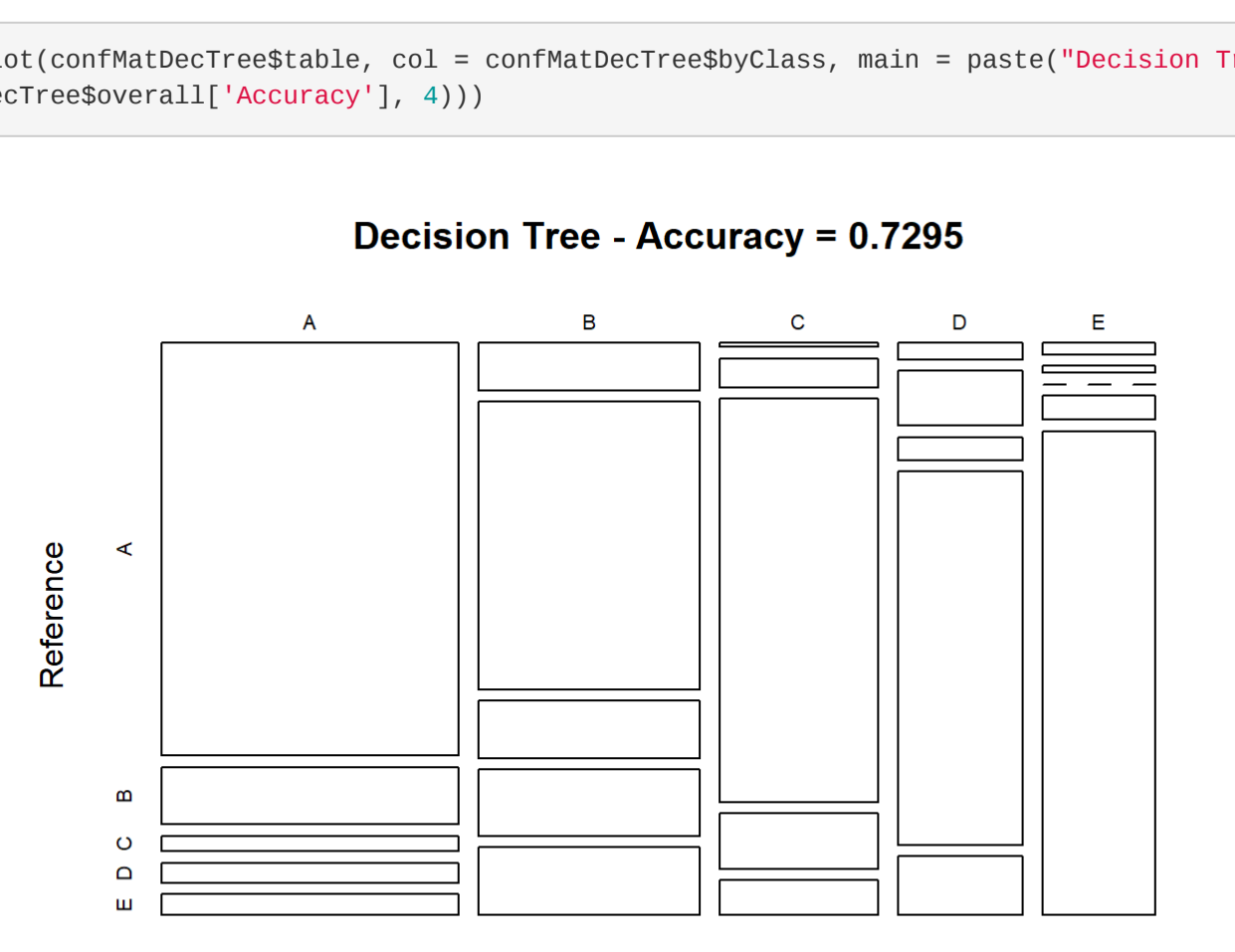
Prediction on Test dataset

```
predictDecTree <- predict(modFitDecTree, newdata=TestSet, type="class")
confMatDecTree <- confusionMatrix(predictDecTree, as.factor(TestSet$classe) )
confMatDecTree
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1497  209   55   73   76
##          B  128  781  156  180  184
##          C    8   56  780  107   68
##          D   25   84   35  571   90
##          E   16    9    0   33  664
##
## Overall Statistics
##
##                Accuracy : 0.7295
##                  95% CI : (0.7179, 0.7408)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.6556
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.8943   0.6857   0.7602  0.59232   0.6137
## Specificity            0.9019   0.8635   0.9508  0.95245   0.9879
## Pos Pred Value         0.7838   0.5465   0.7655  0.70932   0.9197
## Neg Pred Value         0.9555   0.9197   0.9494  0.92264   0.9190
## Prevalence             0.2845   0.1935   0.1743  0.16381   0.1839
## Detection Rate         0.2544   0.1327   0.1325  0.09703   0.1128
## Detection Prevalence   0.3246   0.2428   0.1732  0.13679   0.1227
## Balanced Accuracy      0.8981   0.7746   0.8555  0.77239   0.8008
```

Plot matrix results

```
plot(confMatDecTree$table, col = confMatDecTree$byClass, main = paste("Decision Tree - Accuracy =", round(confMat
DecTree$overall['Accuracy'], 4)))
```



Generalized Boosted Model

Model fit

```
set.seed(301)
controlGBM <- trainControl(method = "repeatedcv", number = 5, repeats = 1)
modFitGBM <- train(classe ~ ., data=TrainSet, method = "gbm", trControl = controlGBM, verbose = FALSE)

modFitGBM$finalModel
```

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

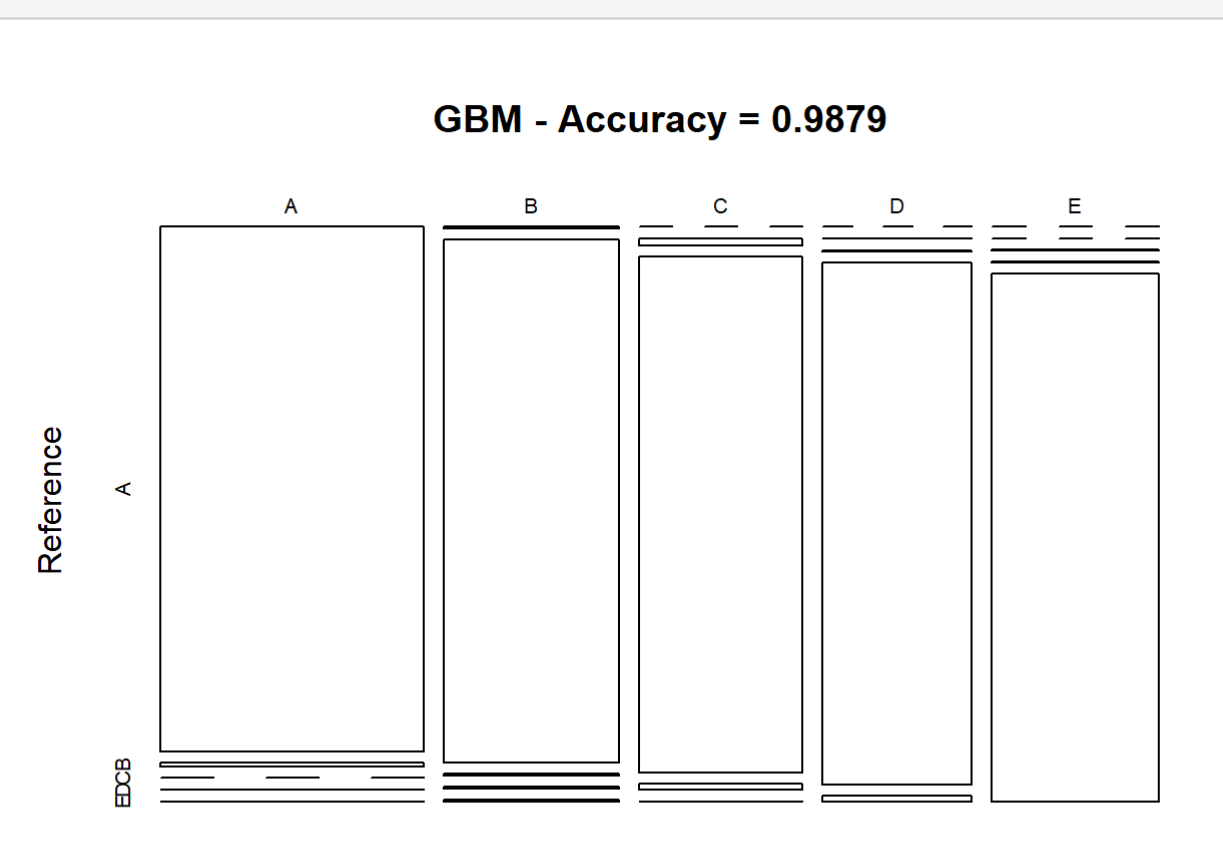
Prediction on Test dataset

```
predictGBM <- predict(modFitGBM, newdata=TestSet)
confMatGBM <- confusionMatrix(predictGBM, as.factor(TestSet$classe) )
confMatGBM
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1671   11    0    2    1
##          B    3 1113    3    4    4
##          C    0   14 1020   12    1
##          D    0    1    2  945   11
##          E    0    0    1    1 1065
##
## Overall Statistics
##
##                Accuracy : 0.9879
##                  95% CI : (0.9848, 0.9906)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9847
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9982   0.9772   0.9942   0.9803   0.9843
## Specificity            0.9967   0.9971   0.9944   0.9972   0.9996
## Pos Pred Value         0.9917   0.9876   0.9742   0.9854   0.9981
## Neg Pred Value         0.9993   0.9945   0.9988   0.9961   0.9965
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2839   0.1891   0.1733   0.1606   0.1810
## Detection Prevalence   0.2863   0.1915   0.1779   0.1630   0.1813
## Balanced Accuracy      0.9974   0.9871   0.9943   0.9887   0.9919
```

Plot matrix results

```
plot(confMatGBM$table, col = confMatGBM$byClass, main = paste("GBM - Accuracy =", round(confMatGBM$overall['Accur
acy'], 4)))
```



Applying the selected model

The accuracy of the 3 regression modeling methods above are:

- Random Forest : 0.9986
- Decision Tree : 0.7295
- GBM : 0.989

In that case, the Random Forest model will be applied to predict the 20 quiz results (testing dataset) as shown below.

```
predictTEST <- predict(modFitRandForest, newdata=testing)
predictTEST
```

```
##  [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
```