Prediction-Assignment-Writeup1

Adittya

May 16, 2020

1. Overview

This document is the final report of the Peer Assessment project from Coursera's course Practical Machine Learning, as part of the Specialization in Data Science. It was built in RStudio, using its knitr functions, meant to be published in html format. This analysis meant to be the basis for the course quiz and a prediction assignment writeup. The main goal of the project is to predict the manner in which 6 participants performed some exercise as described below. This is the "classe" 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.

2. Background

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, your goal will be to use data from accelerometers on the belt, forearm, arm, and dumbell of 6 participants. They were asked to perform barbell lifts correctly and incorrectly in 5 different ways. More information is available from the website here: [http://groupware.les.inf.puc-rio.br/har]http://groupware.les.inf.puc-rio.br/har (see the section on the Weight Lifting Exercise Dataset).

3. Data Loading and Exploratory Analysis

a. 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

b. Environment Setup

```
library(knitr)
library(caret)
```

```
## Loading required package: lattice
```

```
## Loading required package: ggplot2
```

```
library(rpart)
library(rpart.plot)
library(rattle)
```

```
## Rattle: A free graphical interface for data science with R.
## Version 5.3.0 Copyright (c) 2006-2018 Togaware Pty Ltd.
## Type 'rattle()' to shake, rattle, and roll your data.
```

```
library(randomForest)
```

```
## randomForest 4.6-14
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

```
##
## Attaching package: 'randomForest'
```

```
## The following object is masked from 'package:rattle':
##
##     importance
```

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

```
library(corrplot)
```

```
## corrplot 0.84 loaded
```

```
set.seed(301)
```

c. Data Loading and Cleaning

The next step is loading the dataset from the URL provided above. The training dataset is then partinioned 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. Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that generated the plot.

```
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"
```

```r
# downloading 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)

# creating 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
```

```r
dim(TestSet)
```

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

```r
# removing variables with Nearly Zero Variance
NZV <- nearZeroVar(TrainSet)
TrainSet <- TrainSet[, -NZV]
TestSet  <- TestSet[, -NZV]
dim(TestSet)
```

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

```r
dim(TrainSet)
```

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

```r
# removing 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
```

```r
dim(TrainSet)
```

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

```
# removing identification only variables (columns 1 to 5)
TrainSet <- TrainSet[, -(1:5)]
TestSet  <- TestSet[, -(1:5)]
dim(TrainSet)
```

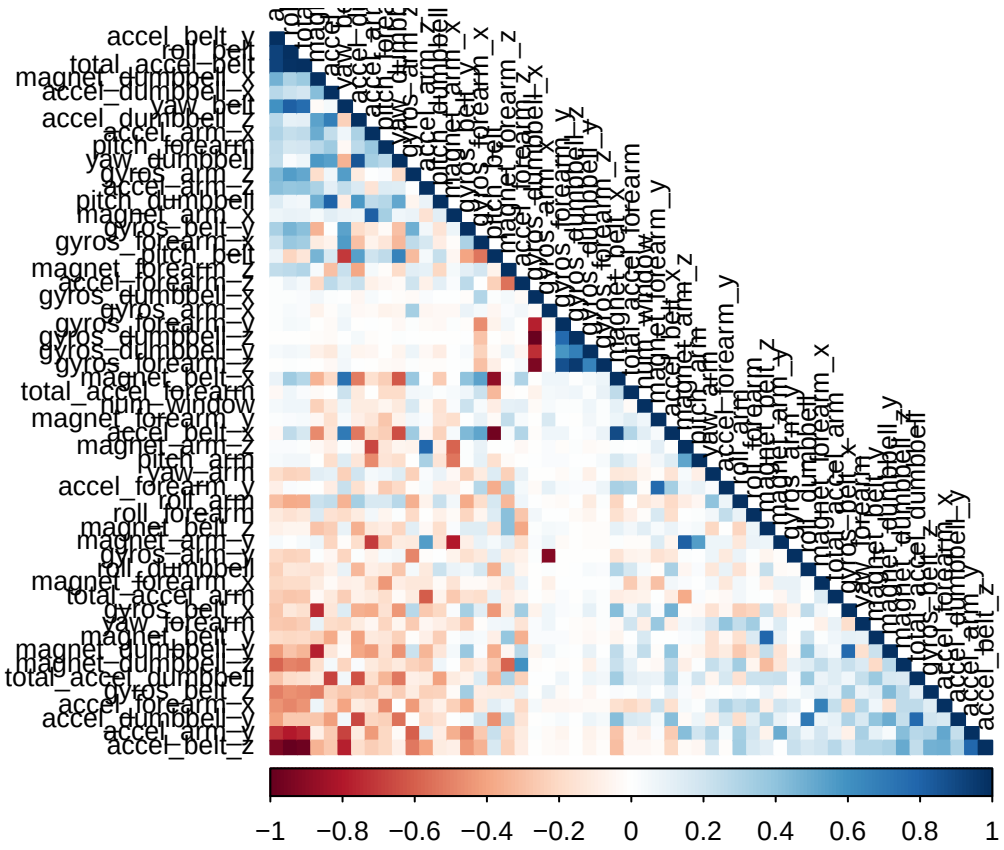
```
## [1] 13737    54
```

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

d.Coorection 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.

4. 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.

a. Random Forests

```
# model fit
set.seed(301)
controlRF <- trainControl(method="cv", number=3, verboseIter=FALSE)
modFitRandForest <- train(classe ~ ., data=TrainSet, method="rf",
                          trControl=controlRF)

modFitRandForest$finalModel
```

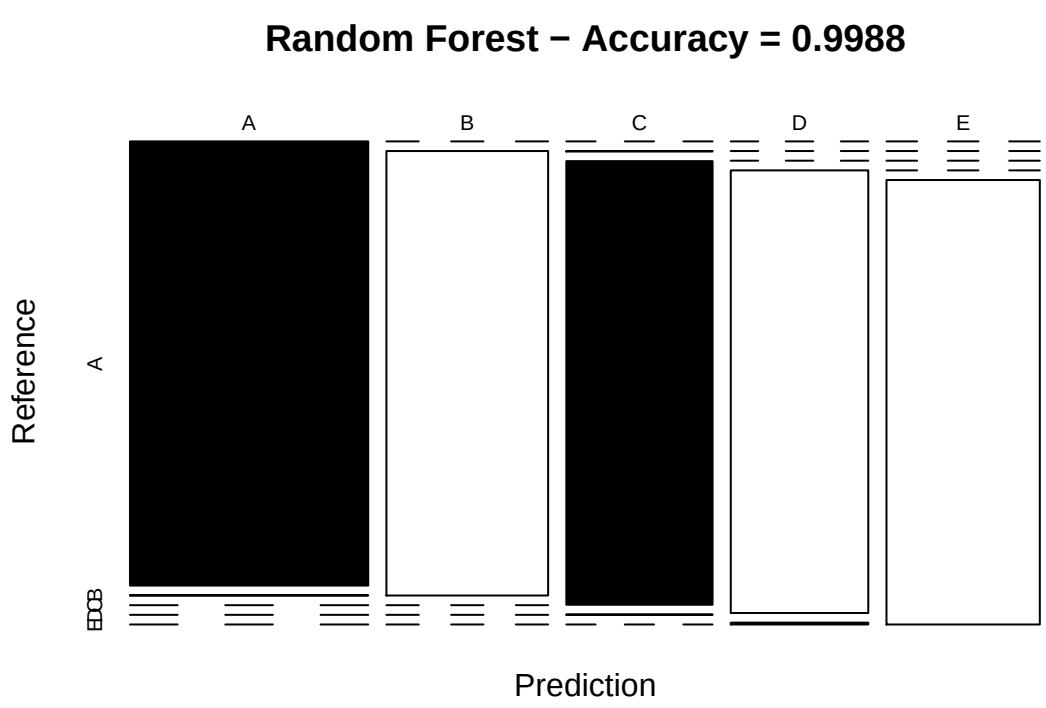
```
##
## Call:
##  randomForest(x = x, y = y, mtry = param$mtry)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 27
##
##         OOB estimate of  error rate: 0.23%
## Confusion matrix:
##      A    B    C    D    E  class.error
## A 3904    1    0    0    1 0.0005120328
## B    6 2648    3    1    0 0.0037622272
## C    0    5 2391    0    0 0.0020868114
## 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, TestSet$classe)
confMatRandForest
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1674    1    0    0    0
##          B    0 1137    0    0    0
##          C    0    1 1026    1    0
##          D    0    0    0  963    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   0.9982   1.0000   0.9990   0.9963
## Specificity            0.9998   1.0000   0.9996   0.9992   1.0000
## Pos Pred Value         0.9994   1.0000   0.9981   0.9959   1.0000
## Neg Pred Value         1.0000   0.9996   1.0000   0.9998   0.9992
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2845   0.1932   0.1743   0.1636   0.1832
## Detection Prevalence   0.2846   0.1932   0.1747   0.1643   0.1832
## Balanced Accuracy      0.9999   0.9991   0.9998   0.9991   0.9982
```

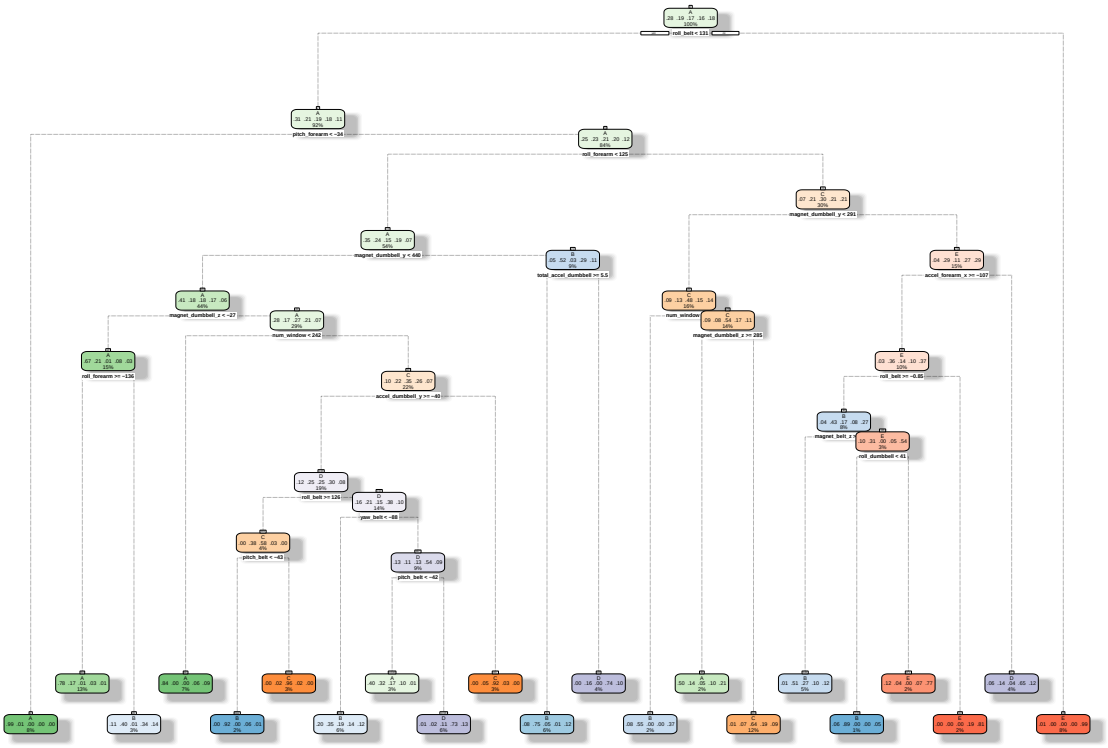
```r
# plotting matrix results
plot(confMatRandForest$table, col = confMatRandForest$byClass,
     main = paste("Random Forest - Accuracy =",
                  round(confMatRandForest$overall['Accuracy'], 4)))
```



#b. Decision Tree

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

```
## Warning: labs do not fit even at cex 0.15, there may be some overplotting
```

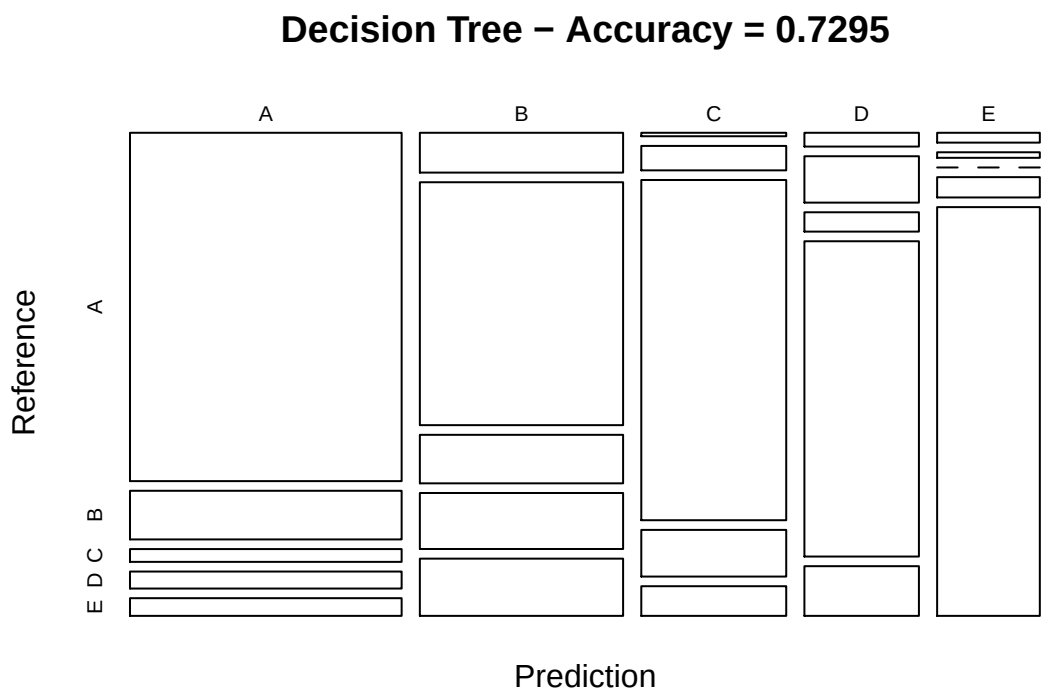



```
# prediction on Test dataset
predictDecTree <- predict(modFitDecTree, newdata=TestSet, type="class")
confMatDecTree <- confusionMatrix(predictDecTree, TestSet$classe)
confMatDecTree
```

```
## 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
```

```r
# plotting matrix results
plot(confMatDecTree$table, col = confMatDecTree$byClass,
     main = paste("Decision Tree - Accuracy =",
                  round(confMatDecTree$overall['Accuracy'], 4)))
```



#c. Generalized Boosted Model (GBM)

```r
# model fit
set.seed(301)
controlGBM <- trainControl(method = "repeatedcv", number = 5, repeats = 1)
modFitGBM  <- train(classe ~ ., data=TrainSet, method = "gbm",
```

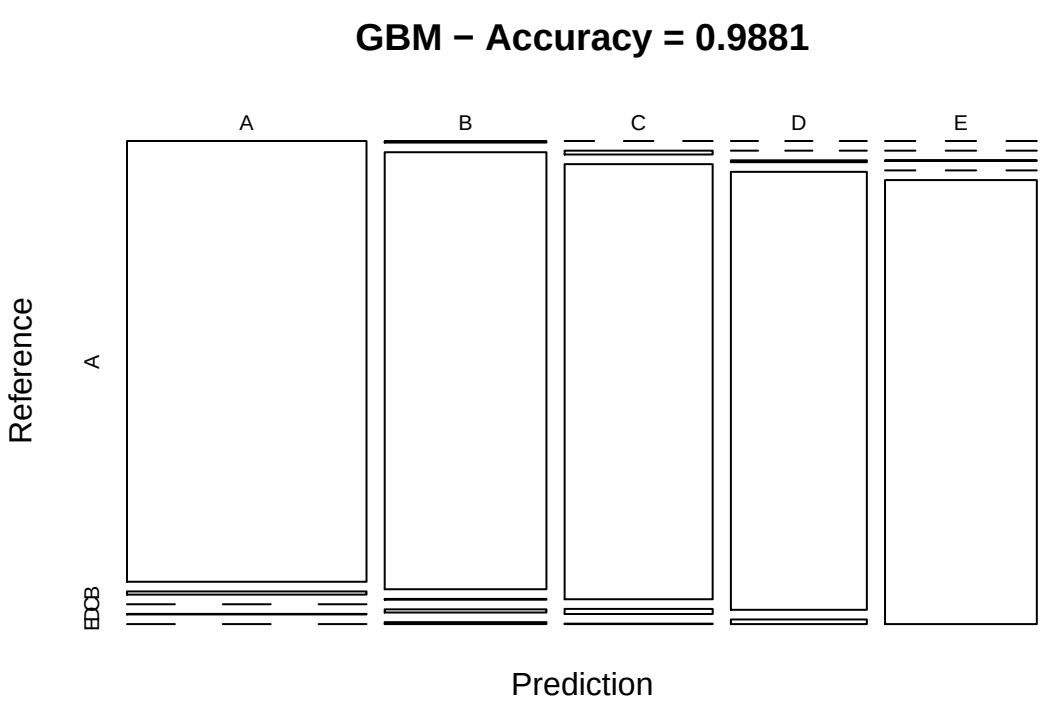
```
                    trControl = controlGBM, verbose = FALSE)

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, TestSet$classe)
confMatGBM
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1670   12    0    2    0
##          B    4 1118    2    8    5
##          C    0    9 1019   12    1
##          D    0    0    4  942   10
##          E    0    0    1    0 1066
##
## Overall Statistics
##
##                Accuracy : 0.9881
##                  95% CI : (0.985, 0.9907)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.985
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9976   0.9816   0.9932   0.9772   0.9852
## Specificity            0.9967   0.9960   0.9955   0.9972   0.9998
## Pos Pred Value         0.9917   0.9833   0.9789   0.9854   0.9991
## Neg Pred Value         0.9990   0.9956   0.9986   0.9955   0.9967
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2838   0.1900   0.1732   0.1601   0.1811
## Detection Prevalence   0.2862   0.1932   0.1769   0.1624   0.1813
## Balanced Accuracy      0.9971   0.9888   0.9943   0.9872   0.9925
```

```
# plotting matrix results
plot(confMatGBM$table, col = confMatGBM$byClass,
     main = paste("GBM - Accuracy =", round(confMatGBM$overall['Accuracy'], 4)))
```



##5. Applying the selected Model to the Test Data The accuracy of the 3 regression modeling methods above are:

Random Forest : 0.9968 Decision Tree : 0.8291 GBM : 0.9884 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
```