Machine Learning Project

Seema

May 29, 2020

Executive summary

We ran the analysis for three models. The accuracy of the 3 regression modeling methods were:

Random Forest : 0.9963 Decision Tree : 0.7368 GBM : 0.9839

Based on the accuracy results,the Random Forest model was applied to predict the 20 quiz results.

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://web.archive.org/web/20161224072740/http:/groupware.les.inf.puc-rio.br/har (http://web.archive.org/web/20161224072740/http:/groupware.les.inf.puc-rio.br/har) (see the section on the Weight Lifting Exercise Dataset).

Data Sources

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)

The data for this project come from http://groupware.les.inf.puc-rio.br/har (http://groupware.les.inf.puc-rio.br/har). Full source:

Velloso, E.; Bulling, A.; Gellersen, H.; Ugulino, W.; Fuks, H. “Qualitative Activity Recognition of Weight Lifting Exercises. Proceedings of 4th International Conference in Cooperation with SIGCHI (Augmented Human ’13)”. Stuttgart, Germany: ACM SIGCHI, 2013.

A short description of the datasets content from the authors' website:

"Six young health participants were asked to perform one set of 10 repetitions of the Unilateral Dumbbell Biceps Curl in five different fashions: exactly according to the specification (Class A), throwing the elbows to the front (Class B), lifting the dumbbell only halfway (Class C), lowering the dumbbell only halfway (Class D) and throwing the hips to the front (Class E).

Class A corresponds to the specified execution of the exercise, while the other 4 classes correspond to common mistakes. Participants were supervised by an experienced weight lifter to make sure the execution complied to the manner they were supposed to simulate. The exercises were performed by six male participants aged between 20-28 years, with little weight lifting experience. We made sure that all participants could easily simulate the mistakes in a safe and controlled manner by using a relatively light dumbbell (1.25kg)."

Data Preperation

```
setwd("C:/Users/snamin/Documents/GitHub/Practical-Machine-Learning")
library(knitr)
library(caret)
library(rpart)
library(rpart.plot)
library(rattle)
library(randomForest)
library(corrplot)
library (gbm)
```

```
## Warning: package 'gbm' was built under R version 3.5.3
```

```
## Loaded gbm 2.1.5
```

```
set.seed(12345)
```

Download the datasets

```
UrlTrain <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"

UrlTest  <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"

training <- read.csv(url(UrlTrain))
testing  <- read.csv(url(UrlTest))
```

Data cleaning and setting a partition

```
inTrain  <- createDataPartition(training$classe, p=0.7, list=FALSE)
TrainSet <- training[inTrain, ]
TestSet  <- training[-inTrain, ]
dim(TrainSet)
```

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

```
# remove variables that are mostly NA

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

dim(TrainSet)
```

```
## [1] 13737   106
```

```
dim(TestSet)
```

```
## [1] 5885  106
```

```
# 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(TrainSet)
```

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

```
dim(TestSet)
```

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

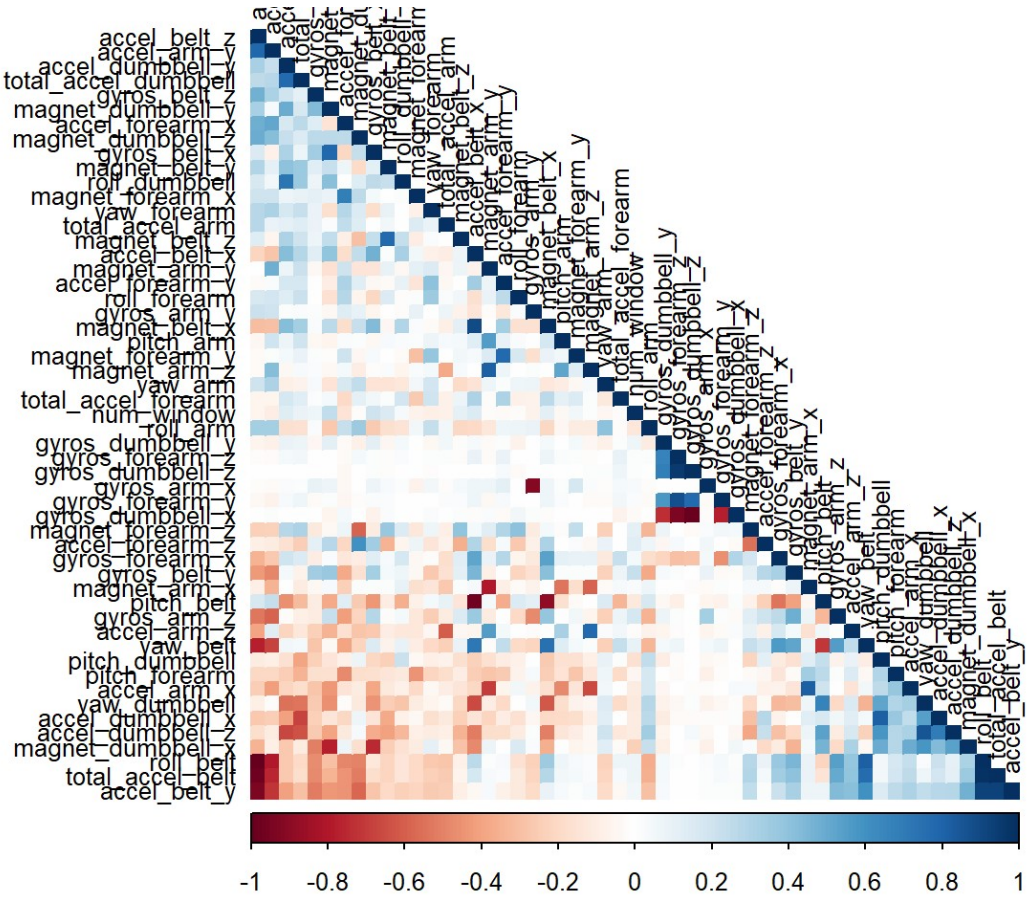
```
# remove identification only variables (columns 1 to 5)

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

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

Correlation Analysis

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



Prediction Model Building Three 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.

Random Forest

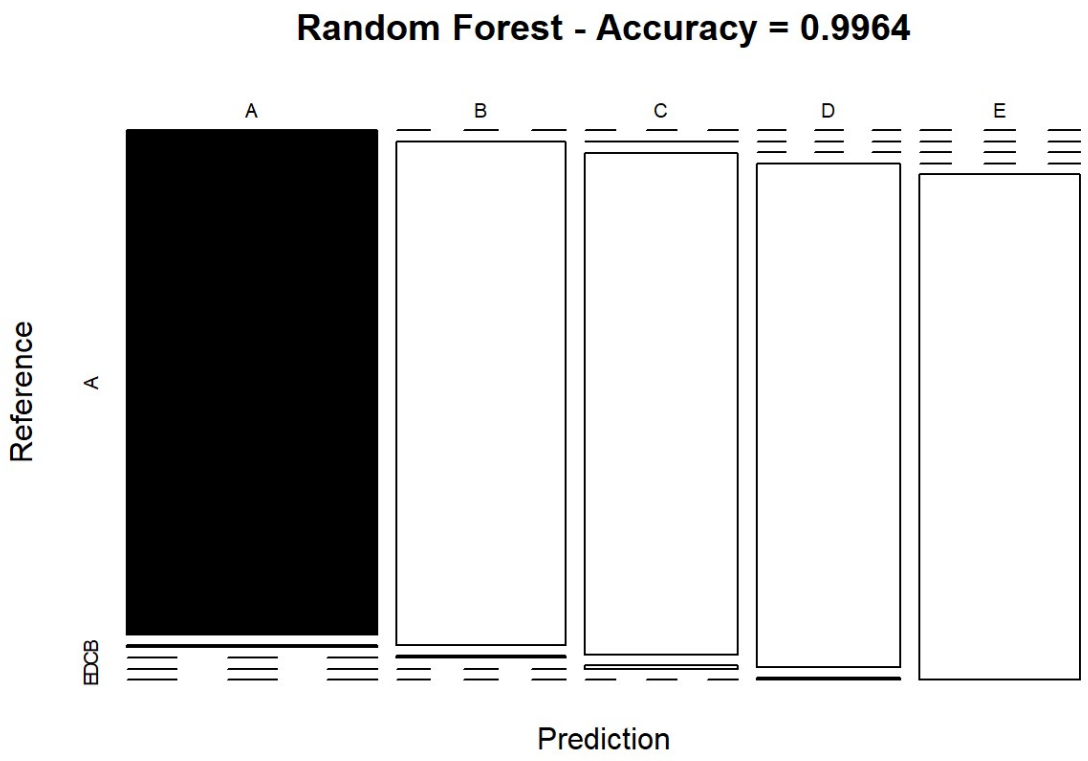
```
set.seed(12345)
controlRF <- trainControl(method="cv", number=3, verboseIter=FALSE)
modFitRandForest <- train(classe ~ ., data=TrainSet, method="rf",
                          trControl=controlRF)
modFitRandForest$finalModel
```

```
##
## 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: 0.2%
## Confusion matrix:
##      A    B    C    D    E  class.error
## A 3904    1    0    0    1 0.0005120328
## B    6 2649    2    1    0 0.0033860045
## C    0    4 2391    1    0 0.0020868114
## D    0    0    7 2245    0 0.0031083481
## E    0    0    0    5 2520 0.0019801980
```

```
# prediction on Test dataset
predictRandForest <- predict(modFitRandForest, newdata=TestSet)
confMatRandForest <- confusionMatrix(predictRandForest, TestSet$classe)
confMatRandForest
```

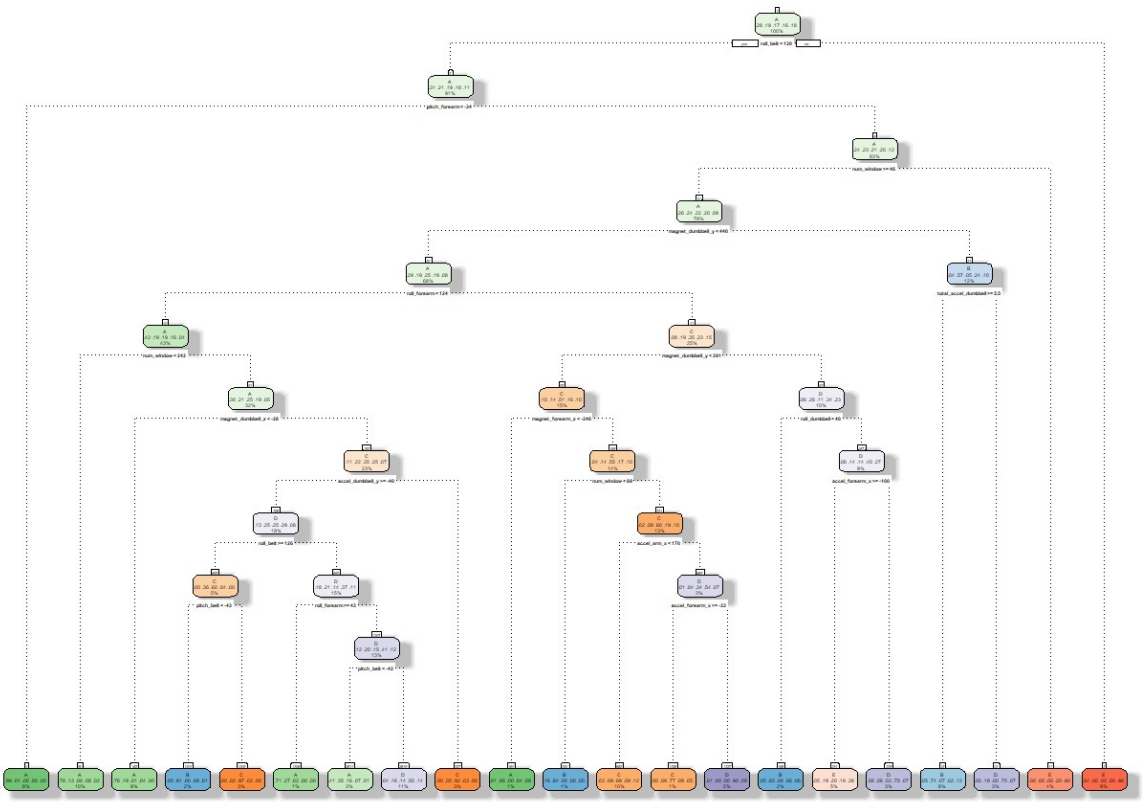
```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1674    5    0    0    0
##          B    0 1133    4    0    0
##          C    0    1 1022    7    0
##          D    0    0    0  957    4
##          E    0    0    0    0 1078
##
## Overall Statistics
##
##                Accuracy : 0.9964
##                  95% CI : (0.9946, 0.9978)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9955
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   0.9947   0.9961   0.9927   0.9963
## Specificity            0.9988   0.9992   0.9984   0.9992   1.0000
## Pos Pred Value         0.9970   0.9965   0.9922   0.9958   1.0000
## Neg Pred Value         1.0000   0.9987   0.9992   0.9986   0.9992
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2845   0.1925   0.1737   0.1626   0.1832
## Detection Prevalence   0.2853   0.1932   0.1750   0.1633   0.1832
## Balanced Accuracy      0.9994   0.9969   0.9972   0.9960   0.9982
```

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



Decision Trees

```
set.seed(12345)
modFitDecTree <- rpart(classe ~ ., data=TrainSet, method="class")
fancyRpartPlot(modFitDecTree)
```

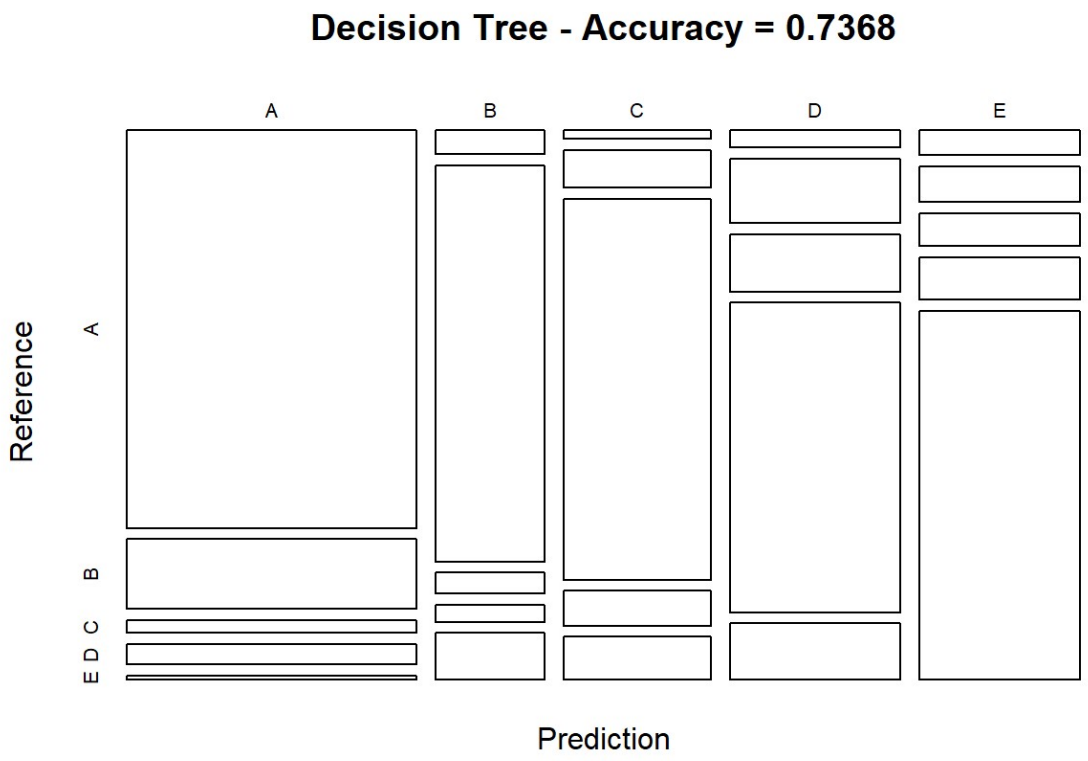


Rattle 2020-May-29 11:15:12 snamin

```
# 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 1530  269   51   79   16
##          B   35  575   31   25   68
##          C   17   73  743   68   84
##          D   39  146  130  702  128
##          E   53   76   71   90  786
##
## Overall Statistics
##
##                Accuracy : 0.7368
##                  95% CI : (0.7253, 0.748)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.6656
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9140  0.50483   0.7242   0.7282   0.7264
## Specificity            0.9014  0.96650   0.9502   0.9100   0.9396
## Pos Pred Value         0.7866  0.78338   0.7543   0.6131   0.7305
## Neg Pred Value         0.9635  0.89051   0.9422   0.9447   0.9384
## Prevalence             0.2845  0.19354   0.1743   0.1638   0.1839
## Detection Rate         0.2600  0.09771   0.1263   0.1193   0.1336
## Detection Prevalence   0.3305  0.12472   0.1674   0.1946   0.1828
## Balanced Accuracy      0.9077  0.73566   0.8372   0.8191   0.8330
```

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



Generalized Boosted Model

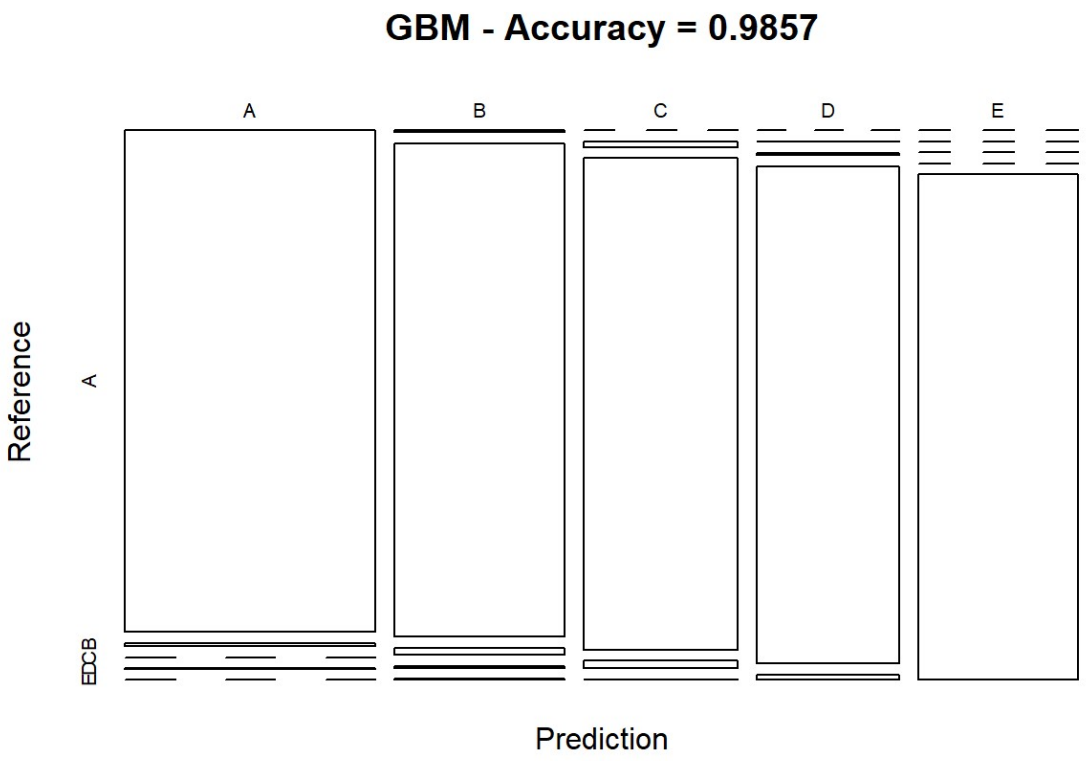
```
# model fit
set.seed(12345)
controlGBM <- trainControl(method = "repeatedcv", number = 5, repeats = 1)
modFitGBM  <- train(classe ~ ., data=TrainSet, method = "gbm",
                    trControl = controlGBM, verbose = FALSE)
modFitGBM$finalModel
```

```
## 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   11    0    2    0
##          B    4 1115   16    5    2
##          C    0   12 1006   16    1
##          D    0    1    4  941   10
##          E    0    0    0    0 1069
##
## Overall Statistics
##
##                Accuracy : 0.9857
##                  95% CI : (0.9824, 0.9886)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9819
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9976   0.9789   0.9805   0.9761   0.9880
## Specificity            0.9969   0.9943   0.9940   0.9970   1.0000
## Pos Pred Value         0.9923   0.9764   0.9720   0.9843   1.0000
## Neg Pred Value         0.9990   0.9949   0.9959   0.9953   0.9973
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2838   0.1895   0.1709   0.1599   0.1816
## Detection Prevalence   0.2860   0.1941   0.1759   0.1624   0.1816
## Balanced Accuracy      0.9973   0.9866   0.9873   0.9865   0.9940
```

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



Applying the Selected Model to the Test Data

Based on the accuracy results,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
```