PRACTICAL MACHINE LEARNING PROJECT: "PREDICTING HUMAN EXERCISE USING SELF-MONITORING DEVICES"

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EXECUTIVE SUMMARY

The emergence of the digital age has been impacted with several technological changes where people are willing to measure their own individual daily activities related to work, exercise, sleep, diet, mood, etc. We are covering ourselves up with these new "gadgets", such as Fitbit, Jawbone Up and Nike FuelBand, which are collecting all this information. These type of devices are part of the quantified self movement and 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 our analysis we carried out an experiment with a group of 6 participants (aged between 20-28 years) using data from accelerometers on the belt, forearm, arm and dumbbell, to build a model to predict the manner in which these participants did the exercise, and then to predict the movement of 20 different test cases.

They were asked to perform barbell lifts correctly and incorrectly in 5 different ways: 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.

More information is available from the website here: http://groupware.les.inf.puc-rio.br/har (see the section on the Weight Lifting Exercise Dataset).

Thus, it is an interesting problem to build a model that predicts what kind of exercise a subject is performing based on the quantitative measurements from self monitoring devices.

Our analysis suggests that our prediction function, developed using the Random Forests method, will have a great accuracy (over 99.70%) to predict the 20 test cases with 100% accuracy.

BASIC SETTING

RStudio

knitr

echo = TRUE

set.seed(12345)

Load libraries:

library(caret) library(rpart) library(rpart.plot) library(rattle) library(RColorBrewer) library(randomForest) library("e1071") library(gbm) library(ggplot2) library(gridExtra).

GETTING AND CLEANING DATA

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

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.

I would like to thank the authors for being very generous in allowing their data to be used for this kind of assignment.

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

The test data are available here: https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv

Downloading and reading the data:

```
trainurl <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
traindata <- read.csv(url(trainurl), na.strings=c("NA","#DIV/0!",""))
dim(traindata)
```

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

```
testurl <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"
validationdata <- read.csv(url(testurl), na.strings=c("NA","#DIV/0!",""))
dim(validationdata)
```

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

Getting a subtraining data set and a subtesting data set from the original training data set to be used for Cross Validation:

Dividing the original traindata set into two subdata sets: 60% in the finaltrain data set and 40% in the finaltest data set. I will perform cross validation within the training division in order to improve the model fit. After that, I will do out-of-sample test with the testing division to validate the model where an expected out-of-sample error rate of less than 0.5%, or 99.5% accuracy, would be acceptable before it is used to perform the prediction on the 20 test cases (that must have 100% accuracy to obtain 20 points awarded). Therefore, I leave the original test set (validationdata) alone, and I will apply our ultimate prediction algorithm to this test set in order to be an unbiased measurement.

```
library (caret)
```

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

```
subtrain <- createDataPartition(traindata$classe, p=0.6, list=FALSE)
finaltrain <- traindata[subtrain, ]
finaltest<- traindata[-subtrain, ]
dim(finaltrain)
```

```
## [1] 11776   160
```

```r
dim(finaltest)
```

```
## [1] 7846  160
```

Cleaning data

I will have a look at these subdata sets and I will call the nearZeroVar function with the argument saveMetrics = TRUE

```r
x = nearZeroVar(finaltrain, saveMetrics = TRUE)
 str(x, vec.len=2)
```

```
## 'data.frame':    160 obs. of  4 variables:
##  $ freqRatio    : num  1 1.07 ...
##  $ percentUnique: num  100 0.051 ...
##  $ zeroVar      : logi  FALSE FALSE FALSE ...
##  $ nzv          : logi  FALSE FALSE FALSE ...
```

```r
y = nearZeroVar(finaltest, saveMetrics = TRUE)
str(y, vec.len=2)
```

```
## 'data.frame':    160 obs. of  4 variables:
##  $ freqRatio    : num  1 1.15 ...
##  $ percentUnique: num  100 0.0765 ...
##  $ zeroVar      : logi  FALSE FALSE FALSE ...
##  $ nzv          : logi  FALSE FALSE FALSE ...
```

By default, a predictor is classified as near-zero variance if the percentage of unique values in the samples is less than 10% and when the frequency ratio mentioned above is greater than 19 (95/5).

We can explore which ones are the zero variance predictors:

```r
x[x[,"zeroVar"] > 0, ]
```

```
##                        freqRatio percentUnique zeroVar  nzv
## kurtosis_yaw_belt              0   0.000000000    TRUE TRUE
## skewness_yaw_belt              0   0.000000000    TRUE TRUE
## amplitude_yaw_belt             0   0.008491848    TRUE TRUE
## kurtosis_yaw_dumbbell          0   0.000000000    TRUE TRUE
## skewness_yaw_dumbbell          0   0.000000000    TRUE TRUE
## amplitude_yaw_dumbbell         0   0.008491848    TRUE TRUE
## kurtosis_yaw_forearm           0   0.000000000    TRUE TRUE
## skewness_yaw_forearm           0   0.000000000    TRUE TRUE
## amplitude_yaw_forearm          0   0.008491848    TRUE TRUE
```

```r
y[y[,"zeroVar"] > 0, ]
```

```
##                        freqRatio percentUnique zeroVar  nzv
## kurtosis_yaw_belt              0    0.00000000    TRUE TRUE
## skewness_yaw_belt              0    0.00000000    TRUE TRUE
```

```
## amplitude_yaw_belt            0    0.01274535    TRUE TRUE
## kurtosis_yaw_dumbbell         0    0.00000000    TRUE TRUE
## skewness_yaw_dumbbell         0    0.00000000    TRUE TRUE
## amplitude_yaw_dumbbell        0    0.01274535    TRUE TRUE
## kurtosis_yaw_forearm          0    0.00000000    TRUE TRUE
## skewness_yaw_forearm          0    0.00000000    TRUE TRUE
## amplitude_yaw_forearm         0    0.01274535    TRUE TRUE
```

and which ones are the near-zero variance predictors:

```
x[x[,"zeroVar"] + x[,"nzv"] > 0, ]
```

```
##                         freqRatio percentUnique zeroVar  nzv
## new_window               43.43774   0.016983696   FALSE TRUE
## kurtosis_yaw_belt         0.00000   0.000000000    TRUE TRUE
## skewness_yaw_belt         0.00000   0.000000000    TRUE TRUE
## amplitude_yaw_belt        0.00000   0.008491848    TRUE TRUE
## avg_roll_arm             56.00000   1.783288043   FALSE TRUE
## stddev_roll_arm          56.00000   1.783288043   FALSE TRUE
## var_roll_arm             56.00000   1.783288043   FALSE TRUE
## avg_pitch_arm            56.00000   1.783288043   FALSE TRUE
## stddev_pitch_arm         56.00000   1.783288043   FALSE TRUE
## var_pitch_arm            56.00000   1.783288043   FALSE TRUE
## avg_yaw_arm              56.00000   1.783288043   FALSE TRUE
## stddev_yaw_arm           57.00000   1.774796196   FALSE TRUE
## var_yaw_arm              57.00000   1.774796196   FALSE TRUE
## amplitude_roll_arm       28.00000   1.715353261   FALSE TRUE
## kurtosis_yaw_dumbbell     0.00000   0.000000000    TRUE TRUE
## skewness_yaw_dumbbell     0.00000   0.000000000    TRUE TRUE
## amplitude_yaw_dumbbell    0.00000   0.008491848    TRUE TRUE
## kurtosis_yaw_forearm      0.00000   0.000000000    TRUE TRUE
## skewness_yaw_forearm      0.00000   0.000000000    TRUE TRUE
## min_roll_forearm         26.00000   1.655910326   FALSE TRUE
## amplitude_roll_forearm   26.00000   1.706861413   FALSE TRUE
## amplitude_yaw_forearm     0.00000   0.008491848    TRUE TRUE
## avg_roll_forearm         26.00000   1.808763587   FALSE TRUE
## stddev_roll_forearm      55.00000   1.791779891   FALSE TRUE
## var_roll_forearm         55.00000   1.791779891   FALSE TRUE
## avg_pitch_forearm        52.00000   1.817255435   FALSE TRUE
## stddev_pitch_forearm     26.00000   1.808763587   FALSE TRUE
## var_pitch_forearm        52.00000   1.817255435   FALSE TRUE
## avg_yaw_forearm          52.00000   1.817255435   FALSE TRUE
## stddev_yaw_forearm       54.00000   1.800271739   FALSE TRUE
## var_yaw_forearm          54.00000   1.800271739   FALSE TRUE
```

```
y[y[,"zeroVar"] + y[,"nzv"] > 0, ]
```

```
##                         freqRatio percentUnique zeroVar  nzv
## new_window               54.64539    0.02549070   FALSE TRUE
## kurtosis_yaw_belt         0.00000    0.00000000    TRUE TRUE
## skewness_yaw_belt         0.00000    0.00000000    TRUE TRUE
## amplitude_yaw_belt        0.00000    0.01274535    TRUE TRUE
```

```
## avg_roll_arm           21.00000    1.54218710   FALSE TRUE
## stddev_roll_arm        21.00000    1.54218710   FALSE TRUE
## var_roll_arm           21.00000    1.54218710   FALSE TRUE
## avg_pitch_arm          21.00000    1.54218710   FALSE TRUE
## stddev_pitch_arm       21.00000    1.54218710   FALSE TRUE
## var_pitch_arm          21.00000    1.54218710   FALSE TRUE
## avg_yaw_arm            21.00000    1.54218710   FALSE TRUE
## stddev_yaw_arm         23.00000    1.51669641   FALSE TRUE
## var_yaw_arm            23.00000    1.51669641   FALSE TRUE
## kurtosis_yaw_dumbbell   0.00000    0.00000000    TRUE TRUE
## skewness_yaw_dumbbell   0.00000    0.00000000    TRUE TRUE
## amplitude_yaw_dumbbell  0.00000    0.01274535    TRUE TRUE
## kurtosis_yaw_forearm    0.00000    0.00000000    TRUE TRUE
## skewness_yaw_forearm    0.00000    0.00000000    TRUE TRUE
## amplitude_yaw_forearm   0.00000    0.01274535    TRUE TRUE
## avg_roll_forearm       31.00000    1.41473362   FALSE TRUE
## stddev_roll_forearm    32.00000    1.40198827   FALSE TRUE
## var_roll_forearm       32.00000    1.40198827   FALSE TRUE
## avg_pitch_forearm      31.00000    1.41473362   FALSE TRUE
## stddev_pitch_forearm   31.00000    1.41473362   FALSE TRUE
## var_pitch_forearm      31.00000    1.41473362   FALSE TRUE
## avg_yaw_forearm        31.00000    1.41473362   FALSE TRUE
## stddev_yaw_forearm     31.00000    1.41473362   FALSE TRUE
## var_yaw_forearm        31.00000    1.41473362   FALSE TRUE
```

```
finalnzvtrain <-finaltrain[, -nearZeroVar(finaltrain)]
dim(finalnzvtrain)
```

1.- I will remove variables with nzv:

```
## [1] 11776   129
```

```
finalnzvtest <-finaltest[, -nearZeroVar(finaltest)]
dim(finalnzvtest)
```

```
## [1] 7846  132
```

```
trainNA <- sapply(finalnzvtrain, function(x) mean(is.na(x))) > 0.95
NoNAtrain <-finalnzvtrain[, trainNA==FALSE]
dim(NoNAtrain)
```

2.- In both data sets (finalnzvtrain and finalnzvtest) there are a lot of NA´s. I will remove variables that are mostly NA´s:

```
## [1] 11776    59
```

```r
testNA <- sapply(finalnzvtest, function(x) mean(is.na(x))) > 0.95
NoNAtest <-finalnzvtest[, testNA==FALSE]
dim(NoNAtest)
```

```
## [1] 7846   59
```

```r
trainclean<-NoNAtrain[, -(1:5)]
testclean<-NoNAtest[, -(1:5)]
dim(trainclean)
```

3.- Having a look at the NoNAtrain and NoNAtest names, I will remove the columns (1:5) which seems to be identification variables.

```
## [1] 11776    54
```

```r
dim(testclean)
```

```
## [1] 7846   54
```

After performing the cleaning data process, we got two data subsets of 54 variables each.

```r
clean1 <- colnames(trainclean)
clean2 <- colnames(trainclean[, -54])  # remove the classe column
testclean2 <- testclean[clean1]       # allow only variables in testclean that are
validation2 <- validationdata[clean2]   # allow only variables in validationdata that are also in train
```

```r
dim(testclean2)
```

4.- Processing validationdata and testclean data sets:

```
## [1] 7846   54
```

```r
dim(validation2)
```

```
## [1] 20 53
```

```r
for (i in 1:length(validation2) ) {
    for(p in 1:length(trainclean)) {
        if( length( grep(names(trainclean[i]), names(validation2)[p]) ) == 1)  {
            class(validation2[p]) <- class(trainclean[i])
        }
    }
}
```

5.- Coerce the data into the same type:

```
validation3 <- rbind(trainclean[2, -54] , validation2)
validationf <- validation3[-1,]
```

6.- Getting the same class between validation2 and trainclean:

PREDICTION MODEL BUILDING

I will use three methods in the training data set (trainclean) to model the regressions and which one that is more accurate, I will apply to the testing set (validationf) and use it for the quiz prediction. These methods are: Decision Trees, Random Forests, and Generalized Boosted Model. Also, I will plot a Confusion Matrix to have a look at the accuracy of these models.

1.- PREDICTION WITH DECISION TREES

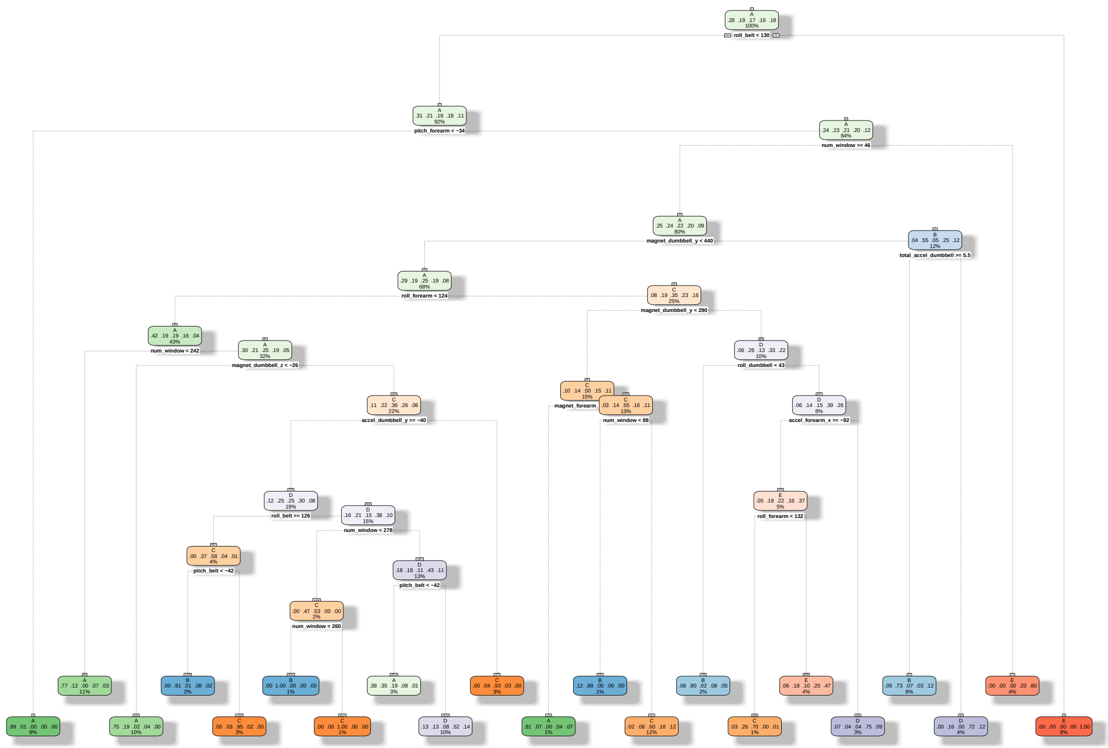
```
set.seed(12345)
library(rpart)
library(rpart.plot)
library(rattle)
```

Fit the model:

```
## Rattle: A free graphical interface for data mining with R.
## Versión 3.4.1 Copyright (c) 2006-2014 Togaware Pty Ltd.
## Escriba 'rattle()' para agitar, sacudir y  rotar sus datos.
```

```
modDC <- rpart(classe ~ ., data=trainclean, method="class")
fancyRpartPlot(modDC)
```

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



Rattle 2016−sep−24 17:02:12 apple

```r
predictionDC <- predict(modDC, testclean2, type = "class")
confusionMatrix(predictionDC, testclean2$classe)
```

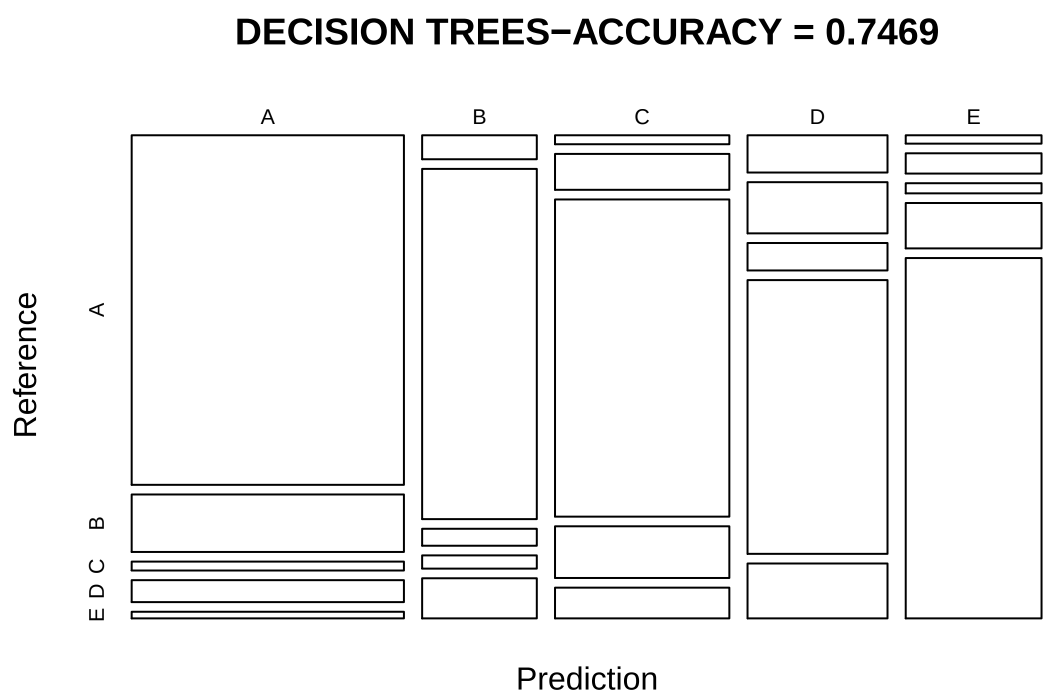
Prediction on Test data set (testclean2):

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 2007  330   51  126   38
##          B   58  847   41   32   97
##          C   33  132 1166  190  113
##          D  110  151   81  808  162
##          E   24   58   29  130 1032
##
## Overall Statistics
##
##                Accuracy : 0.7469
##                  95% CI : (0.7371, 0.7565)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.6785
##  Mcnemar's Test P-Value : < 2.2e-16
##
```

```
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.8992   0.5580   0.8523   0.6283   0.7157
## Specificity            0.9029   0.9640   0.9278   0.9232   0.9624
## Pos Pred Value         0.7864   0.7879   0.7136   0.6159   0.8107
## Neg Pred Value         0.9575   0.9009   0.9675   0.9268   0.9376
## Prevalence             0.2845   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2558   0.1080   0.1486   0.1030   0.1315
## Detection Prevalence   0.3253   0.1370   0.2083   0.1672   0.1622
## Balanced Accuracy      0.9011   0.7610   0.8900   0.7757   0.8390
```

```r
conMatrixDC<-confusionMatrix(predictionDC, testclean2$classe)
```

```r
plot(conMatrixDC$table, col = conMatrixDC$byClass,
     main = paste("DECISION TREES-ACCURACY =",
                  round(conMatrixDC$overall['Accuracy'], 4)))
```



PLOT MATRIX RESULTS:

2.-PREDICTION USING RANDOM FORESTS

```r
set.seed(12345)
ctrRF <- trainControl(method="cv", number=3, verboseIter=FALSE)
modRF <- train(classe ~ ., data=trainclean, method="rf", trControl=ctrRF)
```

Fit the model:

```
## Loading required package: randomForest
## randomForest 4.6-10
## Type rfNews() to see new features/changes/bug fixes.
```

```
modRF$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: 0.25%
## Confusion matrix:
##      A    B    C    D    E  class.error
## A 3345    2    0    0    1 0.0008960573
## B    7 2269    3    0    0 0.0043878894
## C    0    3 2051    0    0 0.0014605648
## D    0    0    4 1925    1 0.0025906736
## E    0    1    0    8 2156 0.0041570439
```

```
predictionRF <- predict(modRF, newdata=testclean2)
confusionMatrix(predictionRF, testclean2$classe)
```

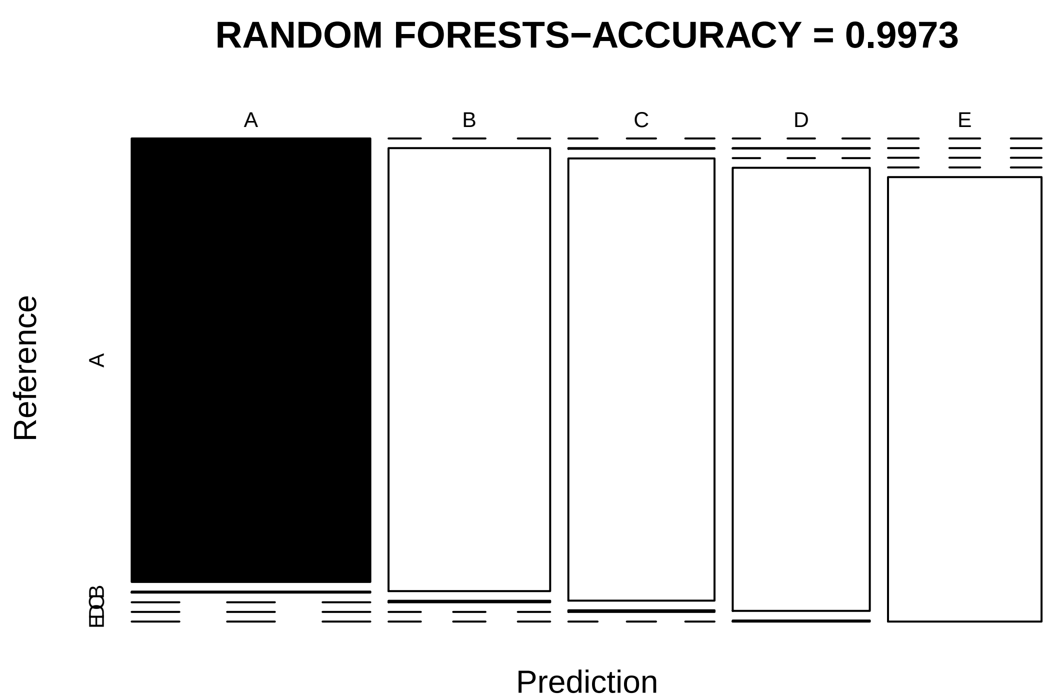
Prediction on Test data set (testclean2):

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 2232    5    0    0    0
##          B    0 1510    5    0    0
##          C    0    2 1363    5    0
##          D    0    1    0 1281    3
##          E    0    0    0    0 1439
##
## Overall Statistics
##
##                Accuracy : 0.9973
##                  95% CI : (0.9959, 0.9983)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9966
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
```

```
## Sensitivity            1.0000   0.9947   0.9963   0.9961   0.9979
## Specificity            0.9991   0.9992   0.9989   0.9994   1.0000
## Pos Pred Value         0.9978   0.9967   0.9949   0.9969   1.0000
## Neg Pred Value         1.0000   0.9987   0.9992   0.9992   0.9995
## Prevalence             0.2845   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2845   0.1925   0.1737   0.1633   0.1834
## Detection Prevalence   0.2851   0.1931   0.1746   0.1638   0.1834
## Balanced Accuracy      0.9996   0.9970   0.9976   0.9978   0.9990
```

```
conMatrixRF <-confusionMatrix(predictionRF, testclean2$classe)
```

```
plot(conMatrixRF$table, col = conMatrixRF$byClass,
     main = paste("RANDOM FORESTS-ACCURACY =",
                  round(conMatrixRF$overall['Accuracy'], 4)))
```



PLOT MATRIX RESULTS:

3.- PREDICTION USING GENERALIZED BOOSTED MODEL

```
set.seed(12345)
ctrGBM<- trainControl(method = "repeatedcv", number = 5, repeats = 1)
modGBM  <- train(classe ~ ., data=trainclean, method = "gbm",
                     trControl = ctrGBM, verbose = FALSE)
```

Fit the model:

```
## Loading required package: gbm
```

```
## Loading required package: survival
##
## Attaching package: 'survival'
##
## The following object is masked from 'package:caret':
##
##     cluster
##
## Loading required package: splines
## Loading required package: parallel
## Loaded gbm 2.1.1
## Loading required package: plyr
```

```
modGBM$finalModel
```

```
## A gradient boosted model with multinomial loss function.
## 150 iterations were performed.
## There were 53 predictors of which 42 had non-zero influence.
```

```
predictionGBM <- predict(modGBM, newdata=testclean2)
confusionMatrix(predictionGBM, testclean2$classe)
```

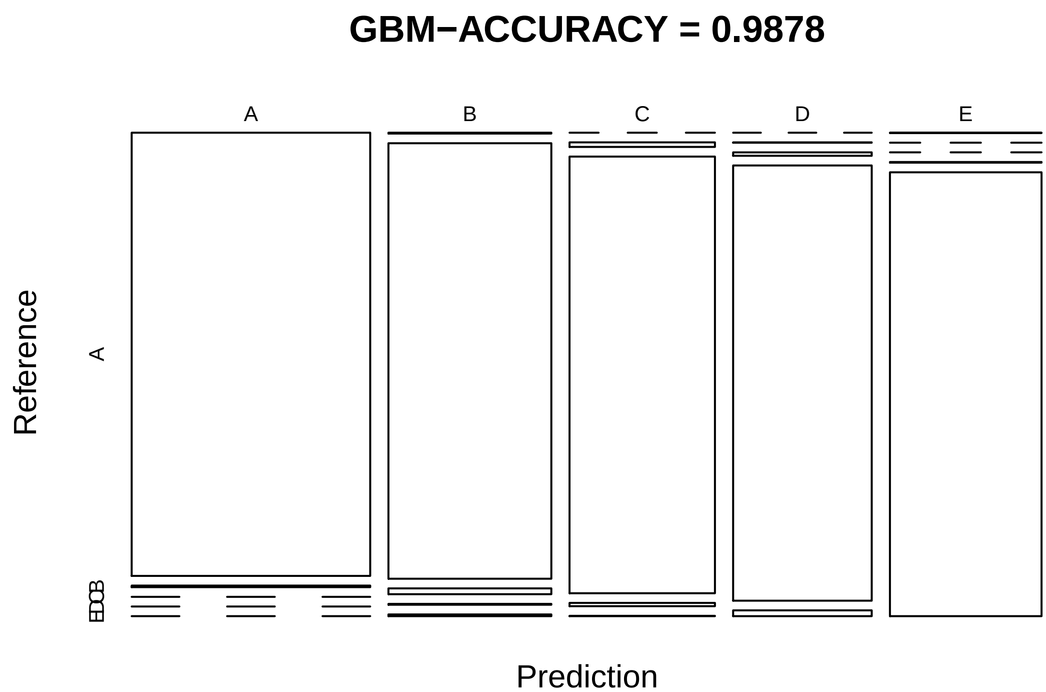
Prediction on Test data set (testclean2):

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 2228    8    0    0    0
##          B    3 1495   20    3    6
##          C    0   14 1338   10    1
##          D    0    1   10 1271   17
##          E    1    0    0    2 1418
##
## Overall Statistics
##
##                Accuracy : 0.9878
##                  95% CI : (0.9851, 0.9901)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9845
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9982   0.9848   0.9781   0.9883   0.9834
## Specificity            0.9986   0.9949   0.9961   0.9957   0.9995
## Pos Pred Value         0.9964   0.9790   0.9817   0.9784   0.9979
```

```
## Neg Pred Value         0.9993   0.9964   0.9954   0.9977   0.9963
## Prevalence             0.2845   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2840   0.1905   0.1705   0.1620   0.1807
## Detection Prevalence   0.2850   0.1946   0.1737   0.1656   0.1811
## Balanced Accuracy      0.9984   0.9899   0.9871   0.9920   0.9914
```

```
conMatrixGBM <-confusionMatrix(predictionGBM, testclean2$classe)
```

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



PLOT MATRIX RESULTS:

APPLYING THE SELECTED MODEL TO THE VALIDATION DATA

```
AccuracyModels<-data.frame(Model=c("DC", "RF", "GBM"),
Accuracy = rbind(conMatrixDC$overall[1], conMatrixRF$overall[1], conMatrixGBM$overall[1]))
print(AccuracyModels)
```

```
##   Model  Accuracy
## 1    DC 0.7468774
## 2    RF 0.9973235
## 3   GBM 0.9877645
```

We can observe that Random Forest has a high accuracy (over 99.70%) and this is the higher of all of these models; cross validation is done with K=3 and the expected out -of-sample error is less than 0.3%. Therefore, I will apply the Random Forest method to the validation data set (validationf) to predict the 20 test cases:

```r
predictionVAL <- predict(modRF, newdata=validationf)
predictionVAL
```

Results (validation dataset):

```
##  [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
```

```r
pml_write_files = function(x) {
        n = length(x)
        for(i in 1:n){
                filename = paste0("problem_id_",i,".txt")
                write.table(x[i], file = filename, quote = FALSE, row.names = FALSE, col.names = FALSE)
        }
}

pml_write_files(predictionVAL)
```

Write the results to a text file for submission:

CONCLUSION

Using exploratory analysis and combining different statistical models, our analysis suggests that our prediction function, developed using the Random Forests method with cross-validation, is be able to have a high accuracy (over 99.70%) to predict the 20 test cases (the manner in which the participants did the exercise) with 100% accuracy (20 points were awarded after submitting the 20 .txt files on the Course Project Submission). Random Forests is the more accurate method for our analysis after comparing it with other different methods such as Decision Trees and Generalized Boosted Model.