Machine Learning Course Project

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Project summary:

The goal of this project is using the data from the study "Qualitative Activity Recognition of Weight Lifting Exercises"" Proceedings of 4th International Conference in Cooperation with SIGCHI to "predict the manner in which they did the exercise." The report should describe: "how you built your model" "how you used cross validation" "what you think the expected out of sample error is" "why you made the choices you did"

Ultimately, the prediction model is to be run on the test data to predict the outcome of 20 different test cases.

Lets us first load all the appropriate packages:

```
library(caret)

## Loading required package: lattice

## Loading required package: ggplot2

library(rpart)
library(rpart.plot)
library(RColorBrewer)
library(rattle)

## Rattle: A free graphical interface for data science with R.
## Version 5.2.0 Copyright (c) 2006-2018 Togaware Pty Ltd.
## Geben Sie 'rattle()' ein, um Ihre Daten mischen.

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
```

```r
library(knitr)
```

DATA INPUT:

```r
set.seed(12345)

trainUrl <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
testUrl <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"

training <- read.csv(url(trainUrl), na.strings=c("NA","#DIV/0!",""))
testing <- read.csv(url(testUrl), na.strings=c("NA","#DIV/0!",""))
```

Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that generated the plot.

```r
inTrain <- createDataPartition(training$classe, p=0.6, list=FALSE)
myTraining <- training[inTrain, ]
myTesting <- training[-inTrain, ]
dim(myTraining); dim(myTesting)

## [1] 11776   160

## [1] 7846  160
```

DATA CLEANING:

```r
nzv <- nearZeroVar(myTraining, saveMetrics=TRUE)
myTraining <- myTraining[,nzv$nzv==FALSE]

nzv<- nearZeroVar(myTesting,saveMetrics=TRUE)
myTesting <- myTesting[,nzv$nzv==FALSE]
myTraining <- myTraining[c(-1)]
```

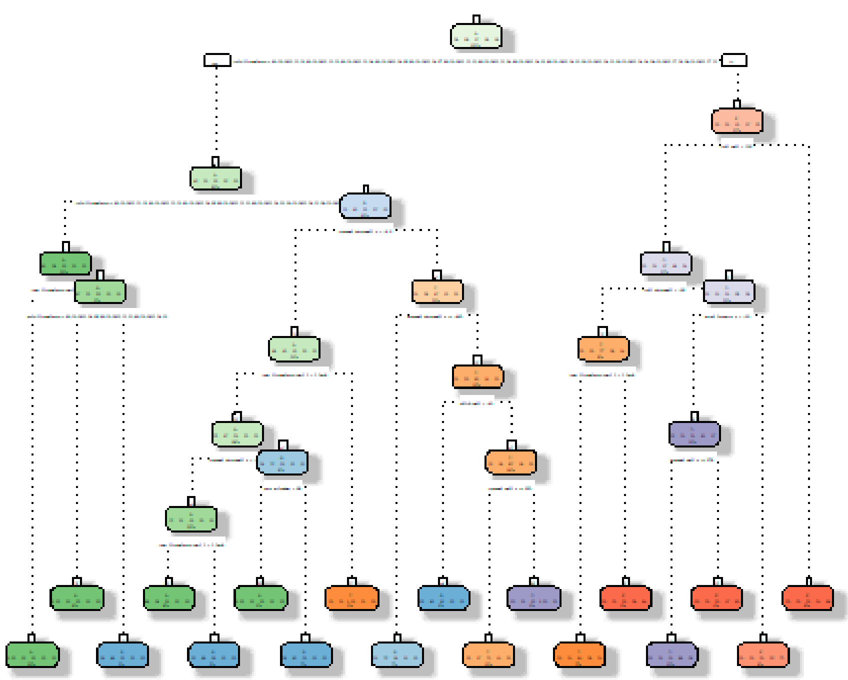
Let us remove the variables that contains missing values (NA) and further transform data to prepare it for prediction:

```r
trainingV3 <- myTraining
for(i in 1:length(myTraining)) {
    if( sum( is.na( myTraining[, i] ) ) /nrow(myTraining) >= .7) {
        for(j in 1:length(trainingV3)) {
            if( length( grep(names(myTraining[i]), names(trainingV3)[j]) ) ==
1)  {
                trainingV3 <- trainingV3[ , -j]
            }
        }
    }
}
myTraining <- trainingV3
rm(trainingV3)
clean1 <- colnames(myTraining)
clean2 <- colnames(myTraining[, -58])
```

```
myTesting <- myTesting[clean1]
testing <- testing[clean2]
dim(myTesting)

## [1] 7846   58

dim(testing)

## [1] 20 57

for (i in 1:length(testing) ) {
    for(j in 1:length(myTraining)) {
        if( length( grep(names(myTraining[i]), names(testing)[j]) ) == 1)  {
            class(testing[j]) <- class(myTraining[i])
        }
    }
}
testing <- rbind(myTraining[2, -58] , testing)
testing <- testing[-1,]
```

PREDTICTION WITH DECISSION TREES:

```
set.seed(12345)
modFitA1 <- rpart(classe ~ ., data=myTraining, method="class")
fancyRpartPlot(modFitA1)

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

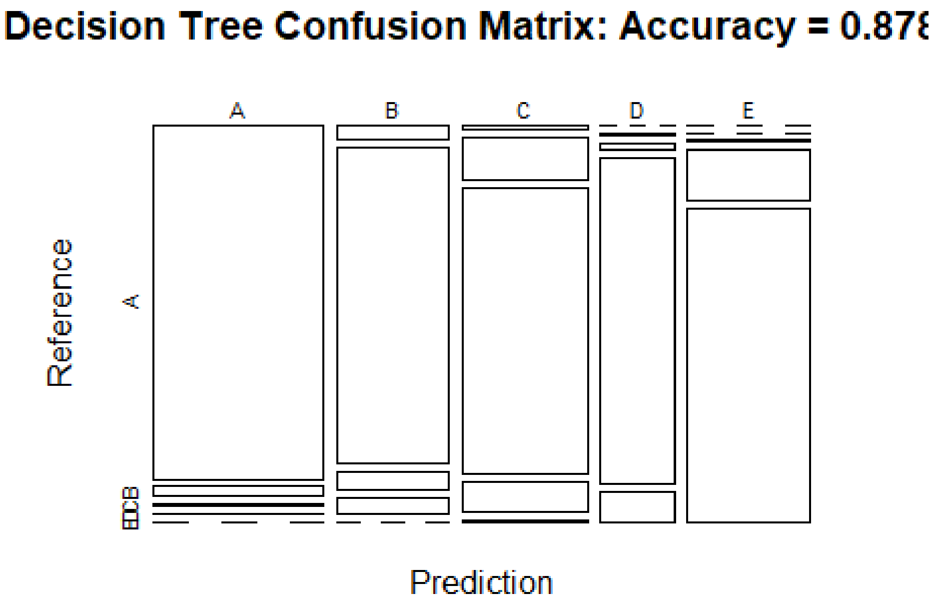


Rattle 2018-Dez-08 19:00:49 Asus

```r
predictionsA1 <- predict(modFitA1, myTesting, type = "class")
cmtree <- confusionMatrix(predictionsA1, myTesting$classe)
cmtree
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 2150   60    7    1    0
##          B   61 1260   69   64    0
##          C   21  188 1269  143    4
##          D    0   10   14  857   78
##          E    0    0    9  221 1360
##
## Overall Statistics
##
##                Accuracy : 0.8789
##                  95% CI : (0.8715, 0.8861)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.8468
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9633   0.8300   0.9276   0.6664   0.9431
## Specificity            0.9879   0.9693   0.9450   0.9845   0.9641
## Pos Pred Value         0.9693   0.8666   0.7809   0.8936   0.8553
## Neg Pred Value         0.9854   0.9596   0.9841   0.9377   0.9869
## Prevalence             0.2845   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2740   0.1606   0.1617   0.1092   0.1733
## Detection Prevalence   0.2827   0.1853   0.2071   0.1222   0.2027
## Balanced Accuracy      0.9756   0.8997   0.9363   0.8254   0.9536
```

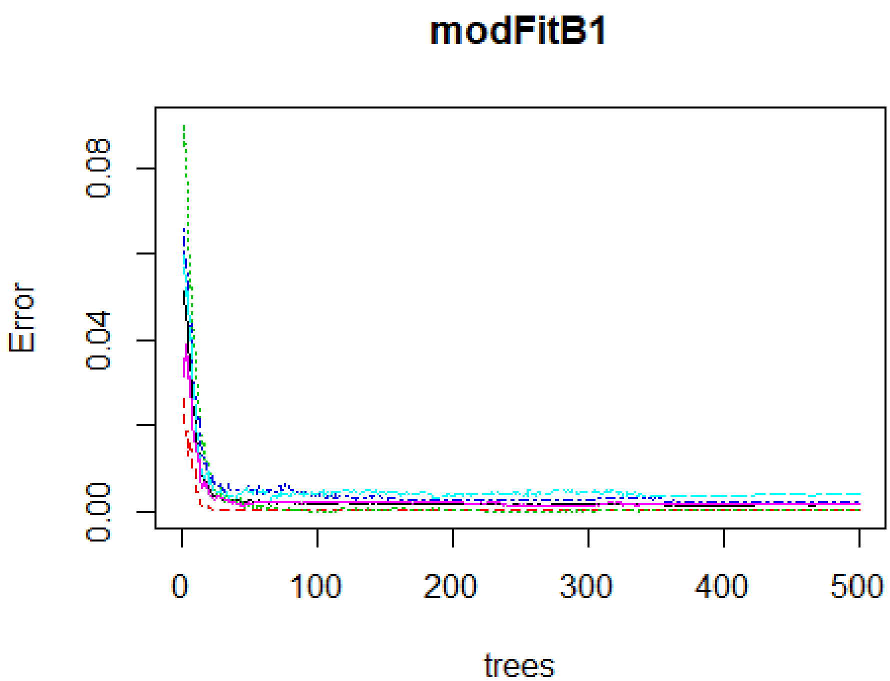
```r
plot(cmtree$table, col = cmtree$byClass, main = paste("Decision Tree
Confusion Matrix: Accuracy =", round(cmtree$overall['Accuracy'], 4)))
```



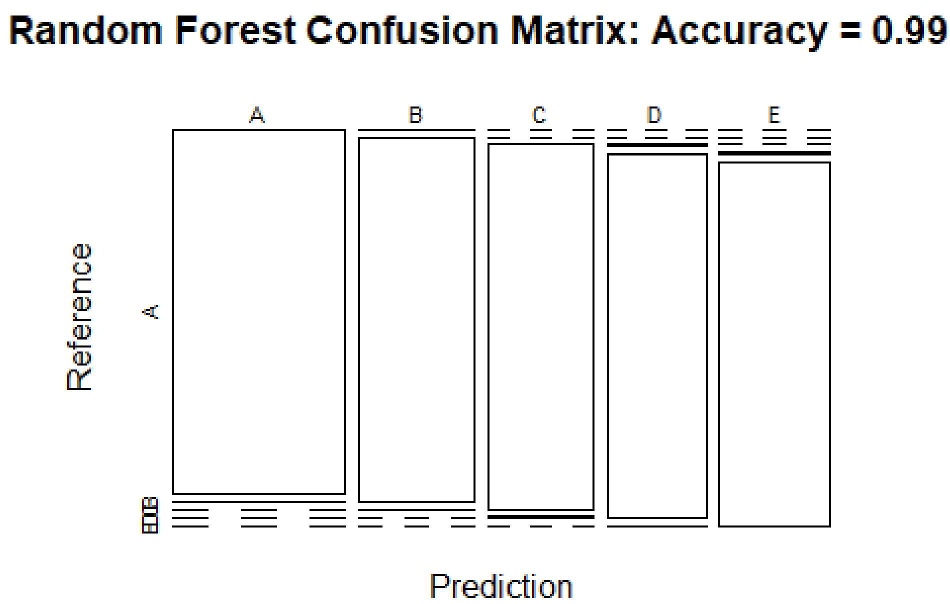
PREDICTION WITH RANDOM FOREST

```
set.seed(12345)
modFitB1 <- randomForest(classe ~ ., data=myTraining)
predictionB1 <- predict(modFitB1, myTesting, type = "class")
cmrf <- confusionMatrix(predictionB1, myTesting$classe)
cmrf

## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 2231    2    0    0    0
##          B    1 1516    1    0    0
##          C    0    0 1366    3    0
##          D    0    0    1 1281    1
##          E    0    0    0    2 1441
##
## Overall Statistics
##
##                Accuracy : 0.9986
##                  95% CI : (0.9975, 0.9993)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9982
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
```

```
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9996   0.9987   0.9985   0.9961   0.9993
## Specificity            0.9996   0.9997   0.9995   0.9997   0.9997
## Pos Pred Value         0.9991   0.9987   0.9978   0.9984   0.9986
## Neg Pred Value         0.9998   0.9997   0.9997   0.9992   0.9998
## Prevalence             0.2845   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2843   0.1932   0.1741   0.1633   0.1837
## Detection Prevalence   0.2846   0.1935   0.1745   0.1635   0.1839
## Balanced Accuracy      0.9996   0.9992   0.9990   0.9979   0.9995

plot(modFitB1)
```




```
plot(cmrf$table, col = cmtree$byClass, main = paste("Random Forest Confusion
Matrix: Accuracy =", round(cmrf$overall['Accuracy'], 4)))
```




```
predictionB2 <- predict(modFitB1, testing, type = "class")
predictionB2
```

```
##  1  2 31  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20
##  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
```

Summary of the final results

Random Forests gave an Accuracy in the myTesting dataset of 99.89%, which was more accurate that Decision Tree analysis. The expected out-of-sample error is 100-99.89 = 0.11%.