Practical Machine Learning Project On Predictive Models

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

Project Introduction

Summary In this project,practical machine learning models are used to predict the manner in which 6 participants conducted their exercise routines.The data is collected with the help of accelerometer attached to the belt,forearm,arm and dumbell of the participants.

Data The training data for the project was downloaded from: https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv

The test data for the project was downloaded from: https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv

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

The goal of your project is to predict the manner in which they did the exercise.Also the prediction modelis used to predict 20 different test cases.

Getting and loading the data

```
set.seed(12345)
trainingUrl <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
testingUrl <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"
training <- read.csv(url(trainingUrl), na.strings=c("NA","#DIV/0!",""))
testing <- read.csv(url(testingUrl), na.strings=c("NA","#DIV/0!",""))
```

Splitting the training set into two sets:

```
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
```

Cleaning the data

Remove variables that have almost zero variance

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

Remove the first column of the myTraining data set

```
myTraining <- myTraining[c(-1)]
```

Clean variables with more than 60% NA

```
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]
            }
        }
    }
}
# Set back to the original variable name
myTraining <- trainingV3
rm(trainingV3)
```

Transform the myTesting and testing data sets

```
clean1 <- colnames(myTraining)
clean2 <- colnames(myTraining[, -58])  # remove the classe column
myTesting <- myTesting[clean1]         # allow only variables in myTesting that are also in myTraining
testing <- testing[clean2]             # allow only variables in testing that are also in myTraining
dim(myTesting)
```

```
## [1] 7846   58
```

```
dim(testing)
```

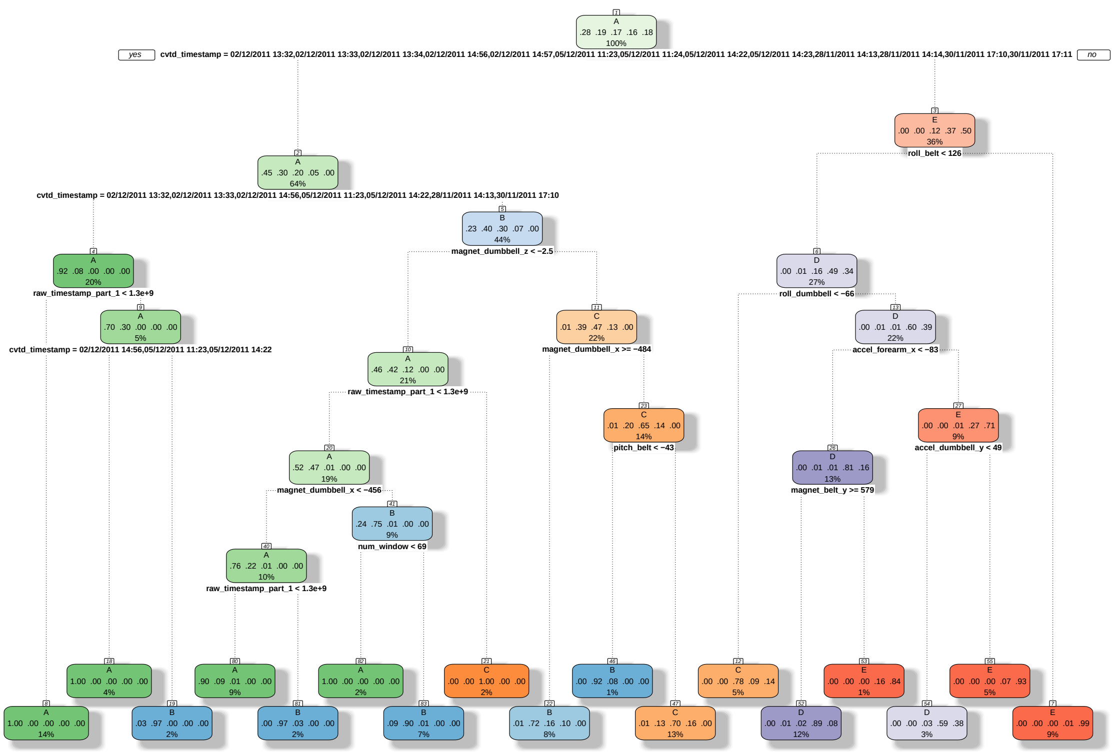
```
## [1] 20 57
```

Coerce the data into the same type

```
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])
        }
    }
}
# To get the same class between testing and myTraining
testing <- rbind(myTraining[2, -58] , testing)
testing <- testing[-1,]
```

Prediction with Decision Trees

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



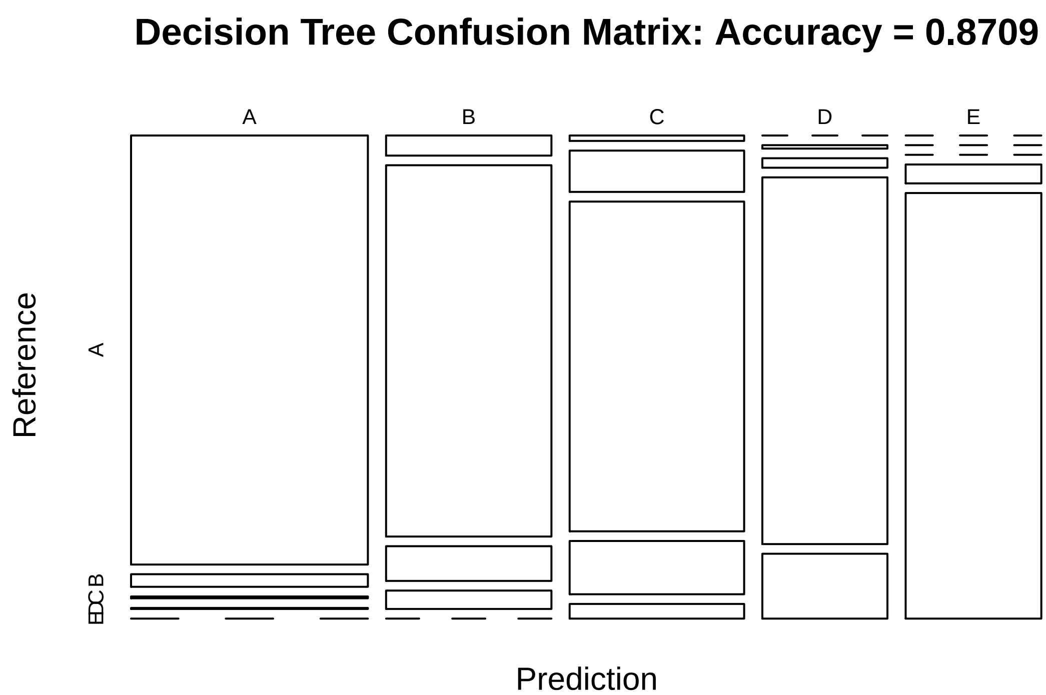
Rattle 2021−May−17 12:28:47 USER

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

```
## Confusion Matrix and Statistics
```

```
##
##           Reference
## Prediction    A    B    C    D    E
##          A 2142   63    9    5    0
##          B   70 1294  121   64    0
##          C   20  152 1213  196   54
##          D    0    9   25  967  171
##          E    0    0    0   54 1217
##
## Overall Statistics
##
##                Accuracy : 0.8709
##                  95% CI : (0.8633, 0.8782)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.8367
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9597   0.8524   0.8867   0.7519   0.8440
## Specificity            0.9863   0.9597   0.9349   0.9688   0.9916
## Pos Pred Value         0.9653   0.8354   0.7419   0.8251   0.9575
## Neg Pred Value         0.9840   0.9644   0.9750   0.9522   0.9658
## Prevalence             0.2845   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2730   0.1649   0.1546   0.1232   0.1551
## Detection Prevalence   0.2828   0.1974   0.2084   0.1494   0.1620
## Balanced Accuracy      0.9730   0.9061   0.9108   0.8603   0.9178
```

```
plot(cmtree$table, col = cmtree$byClass, main = paste("Decision Tree Confusion Matrix: Accuracy =", rou
```



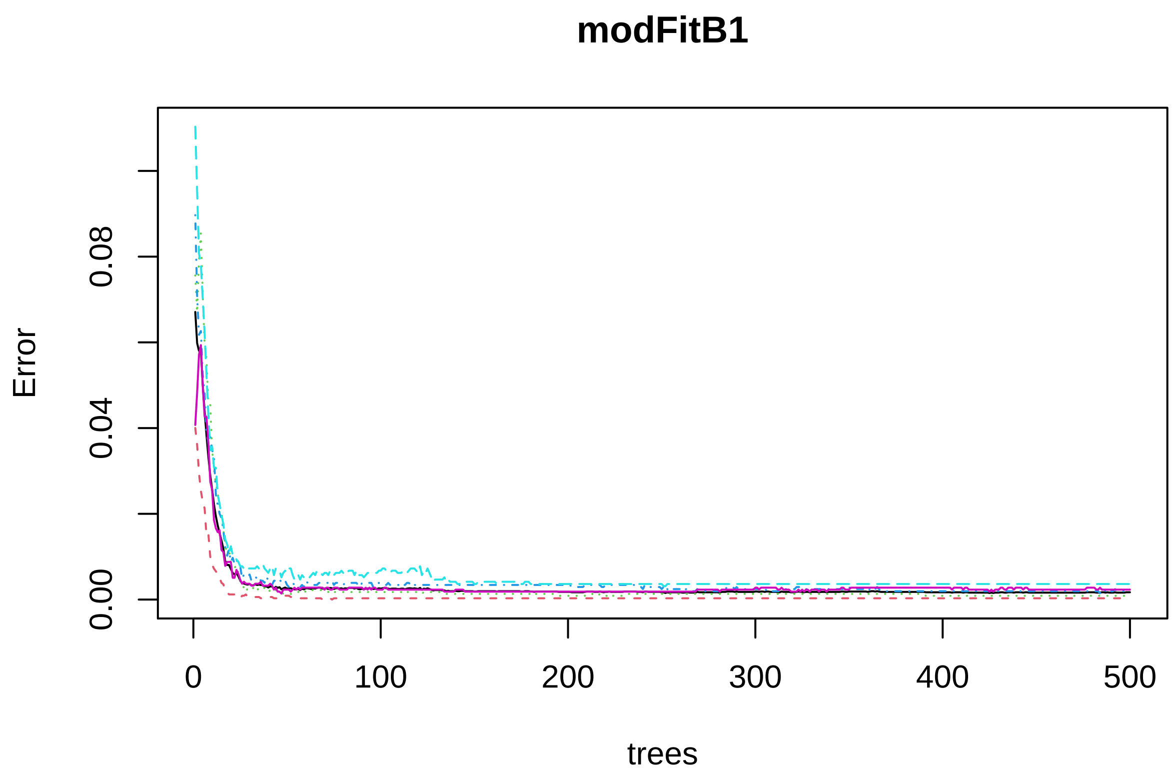
Prediction with Random Forests

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

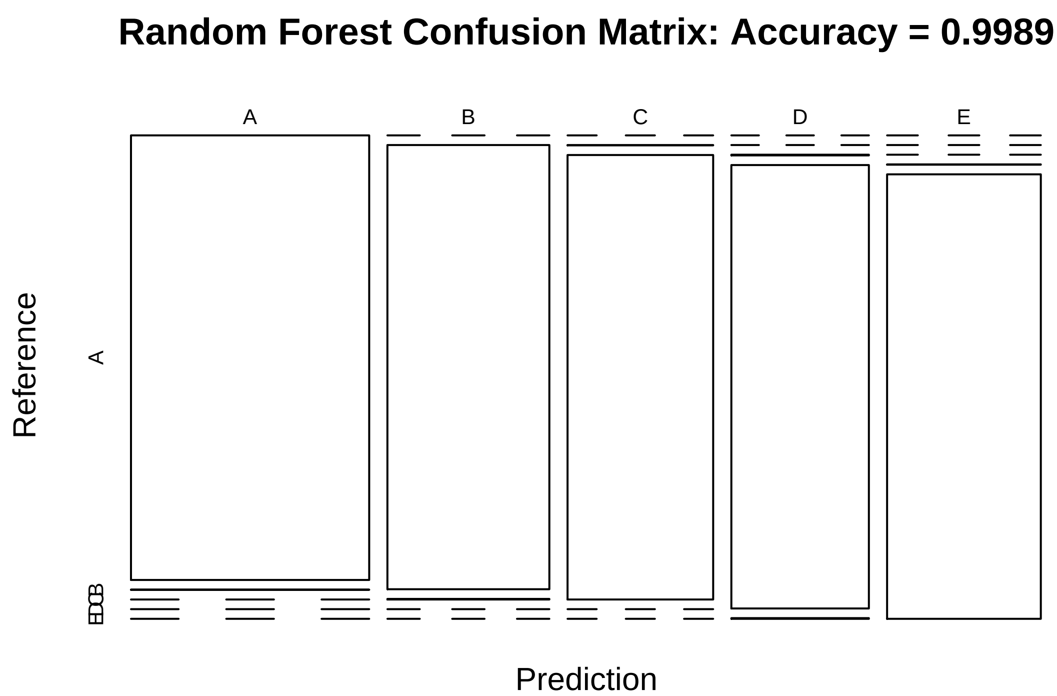
```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 2232    1    0    0    0
##          B    0 1516    2    0    0
##          C    0    1 1364    0    0
##          D    0    0    2 1285    2
##          E    0    0    0    1 1440
##
## Overall Statistics
##
##                Accuracy : 0.9989
##                  95% CI : (0.9978, 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   0.9987   0.9971   0.9992   0.9986
## Specificity            0.9998   0.9997   0.9998   0.9994   0.9998
## Pos Pred Value         0.9996   0.9987   0.9993   0.9969   0.9993
## Neg Pred Value         1.0000   0.9997   0.9994   0.9998   0.9997
## Prevalence             0.2845   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2845   0.1932   0.1738   0.1638   0.1835
## Detection Prevalence   0.2846   0.1935   0.1740   0.1643   0.1837
## Balanced Accuracy      0.9999   0.9992   0.9985   0.9993   0.9992
```

```
plot(modFitB1)
```



```r
plot(cmrf$table, col = cmtree$byClass, main = paste("Random Forest Confusion Matrix: Accuracy =", round
```



Predicting Results on the Test Data

Random Forests gave an Accuracy in the myTesting dataset of 99.89%, which was more accurate that what I got from the Decision Trees or GBM. The expected out-of-sample error is 100-99.89 = 0.11%.

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

```
##  1 21  3  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
```