Practical Machine Learning Project

This document was produced for the course project of 'Practical Machine Learning', the 8th course in the 'Data Science Specialization', a MOOC on Coursera. The code in this report has been developed and tested on a machine running Ubuntu 14.04 and R 3.2.2.

Background

This report outlines the exploratory data analysis conducted on the 'Weight Lifting Exercises' dataset in R, details of which can be found here. The manual notes that '*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.*'

The goal is to predict the type of exercise conducted from the five classes mentioned earlier. Multiple measurements were made using accelerometers in the fore arm, upper arm, waist and dumb-bells. These measured values constitute the predictors.

Data Sources

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

Getting the data

First, I assign the URL's provided earlier to variables that I can access in R.

```
trUrl <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
teUrl <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"
```

In an exploratory data analysis (not reported here) it was found that the missing data in this dataset can take one of three values. They are appropriately identified while inputing the data

```
train <- read.csv(url(trUrl), na.strings=c("NA","#DIV/0!",""))
test <- read.csv(url(teUrl), na.strings=c("NA","#DIV/0!",""))
```

```
dim(train)
```

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

```
summary(train)
```

A summary of the dataset (output suppressed here for brevity) shows that in additon to some columns with entirely missing data, a large number of columns contain $\sim$ 19000 NA's (19216, to be precise). These predictors are there unusable as missing values vastly outnumber the non-missing or provided data, i.e. imputing these values isn't feasible. All these columns are excluded

```r
train <- train[,colSums(is.na(train)) < 19216]
```

Finally, the first column (containing ID's) and the fifth column (containing timestamps) are excluded as predictors

```r
train <- train[,-c(1,5)]
```

Now, using the package *caret*, the dataset is divided into *testing* and *training* sets, following the 40/60 split suggested in the lectures.

```r
library(caret)
```

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

```r
inTrain <- createDataPartition(y=train$classe, p=0.6, list=FALSE)
myTrain <- train[inTrain, ]; myTest <- train[-inTrain, ]
dim(myTrain); dim(myTest)
```

```
## [1] 11776    58
```

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

Machine Learning Models

Now that the data had been formatted, machine learning models are developed to be able to predict the *classe* variable from the 57 predictors that have been short listed. Given the non-linear nature of the data, decision tree based algorithms are used to construct the models. The machine learning algorithms are trained on the *training* set. In the next section, their predictions on the *testing* set are compared. ## Decision Trees

```r
library(rpart)
DTfit <- rpart(classe ~ ., data=myTrain, method="class")
```

Decision trees have an advantage in that you can view the results directly using the following commands (output suppressed here).

```r
library(rattle)
```

```
## Loading required package: RGtk2
## Rattle: A free graphical interface for data mining with R.
## Version 3.5.0 Copyright (c) 2006-2015 Togaware Pty Ltd.
## Type 'rattle()' to shake, rattle, and roll your data.
```

```r
library(rpart.plot)
library(RColorBrewer)
#fancyRpartPlot(DTfit)
```

Random Forests

```r
library(randomForest)
```

```
## randomForest 4.6-12
## Type rfNews() to see new features/changes/bug fixes.
```

```r
RFfit <- randomForest(classe ~ ., data=myTrain, method="class")
```

The importance of the predictors to the accuracy of the model can be visualized using *varImpPlot* command.

```r
#varImpPlot(RFfit)
```

Comparison of model performance

To evaluate the accuracy of the models, their performance on the *test* set is computed

```r
predictDT <- predict(DTfit, myTest, type = "class")
predictRF <- predict(RFfit, myTest, type = "class")
```

Now we look at the respective confusion matrices for the two models

```r
confusionMatrix(predictDT, myTest$classe)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 2107  147   27   17   18
##          B   64 1096   47   14   22
##          C    4   66 1161   66   93
##          D   49  109   46 1035  112
##          E    8  100   87  154 1197
##
## Overall Statistics
##
##                Accuracy : 0.8407
##                  95% CI : (0.8324, 0.8487)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.7983
##  Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9440   0.7220   0.8487   0.8048   0.8301
## Specificity            0.9628   0.9768   0.9646   0.9518   0.9455
## Pos Pred Value         0.9098   0.8817   0.8353   0.7661   0.7743
## Neg Pred Value         0.9774   0.9361   0.9679   0.9614   0.9611
## Prevalence             0.2845   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2685   0.1397   0.1480   0.1319   0.1526
## Detection Prevalence   0.2952   0.1584   0.1772   0.1722   0.1970
## Balanced Accuracy      0.9534   0.8494   0.9067   0.8783   0.8878
```

```r
confusionMatrix(predictRF, myTest$classe)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 2232    5    0    0    0
##          B    0 1513    4    0    0
##          C    0    0 1364    2    0
##          D    0    0    0 1284    3
##          E    0    0    0    0 1439
##
## Overall Statistics
##
##                Accuracy : 0.9982
##                  95% CI : (0.997, 0.999)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9977
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   0.9967   0.9971   0.9984   0.9979
## Specificity            0.9991   0.9994   0.9997   0.9995   1.0000
## Pos Pred Value         0.9978   0.9974   0.9985   0.9977   1.0000
## Neg Pred Value         1.0000   0.9992   0.9994   0.9997   0.9995
## Prevalence             0.2845   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2845   0.1928   0.1738   0.1637   0.1834
## Detection Prevalence   0.2851   0.1933   0.1741   0.1640   0.1834
## Balanced Accuracy      0.9996   0.9980   0.9984   0.9990   0.9990
```