Practical Machine Learning Course Project

CHE PAKRUL AZMI

June 3, 2017

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(Velloso et al. 2013). They were asked to perform barbell lifts correctly and incorrectly in 5 different ways. 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).

Data

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]

The data for this project come from this source: [http://groupware.les.inf.puc-rio.br/har]. If you use the document you create for this class for any purpose please cite them as they have been very generous in allowing their data to be used for this kind of assignment.

Packages, Libraries, Seed

Installing packages, loading libraries, and setting the seed for reproduceability:

```
library(caret)
```

```
library(randomForest) #Random forest for classification and regression
```

```
library(rpart) # Regressive Partitioning and Regression trees
library(rpart.plot) # Decision Tree plot
# setting the overall seed for reproduceability
set.seed(1234)
```

Loading data sets and preliminary cleaning

First we want to load the data sets into R and make sure that missing values are coded correctly. Irrelevant variables will be deleted.

Results will be hidden from the report for clarity and space considerations.

```r
# After saving both data sets into my working directory
# Some missing values are coded as string "#DIV/0!" or "" or "NA" - these will be changed to NA.
# We notice that both data sets contain columns with all missing values - these will be deleted.

# Loading the training data set into my R session replacing all missing with "NA"

library(RCurl)
train_url <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
test_url <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"

trainingset <- read.csv(text=getURL(train_url), na.strings=c("NA","#DIV/0!", ""))


# Loading the testing data set
testingset <- read.csv(text=getURL(test_url), na.strings=c("NA","#DIV/0!", ""))

# Check dimensions for number of variables and number of observations
dim(trainingset)
```

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

```r
dim(testingset)
```

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

```r
# Delete columns with all missing values
trainingset<-trainingset[,colSums(is.na(trainingset)) == 0]
testingset <-testingset[,colSums(is.na(testingset)) == 0]

# Some variables are irrelevant to our current project: user_name, raw_timestamp_part_1, raw_timestamp_
trainingset   <-trainingset[,-c(1:7)]
testingset <-testingset[,-c(1:7)]

# and have a look at our new datasets:
dim(trainingset)
```

```
## [1] 19622    53
```

```r
dim(testingset)
```

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

Partitioning the training data set to allow cross-validation

The training data set contains 53 variables and 19622 obs. The testing data set contains 53 variables and 20 obs. In order to perform cross-validation, the training data set is partionned into 2 sets: subTraining (75%) and subTest (25%). This will be performed using random subsampling without replacement.

```r
subsamples <- createDataPartition(y=trainingset$classe, p=0.75, list=FALSE)
subTraining <- trainingset[subsamples, ]
subTesting <- trainingset[-subsamples, ]
dim(subTraining)
```

```
## [1] 14718    53
```

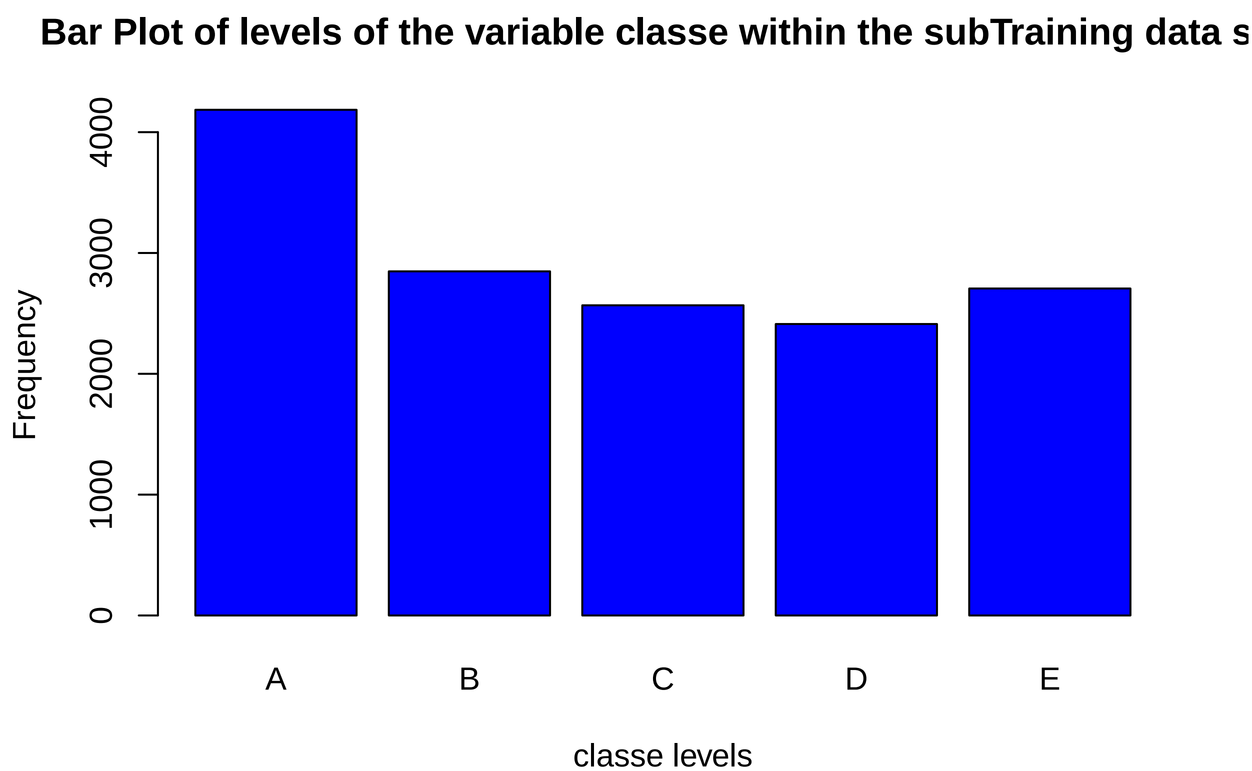
```r
dim(subTesting)
```

```
## [1] 4904   53
```

A look at the Data

The variable "classe" contains 5 levels: A, B, C, D and E. A plot of the outcome variable will allow us to see the frequency of each levels in the subTraining data set and compare one another.

```r
plot(subTraining$classe, col="blue", main="Bar Plot of levels of the variable classe within the subTrai
```



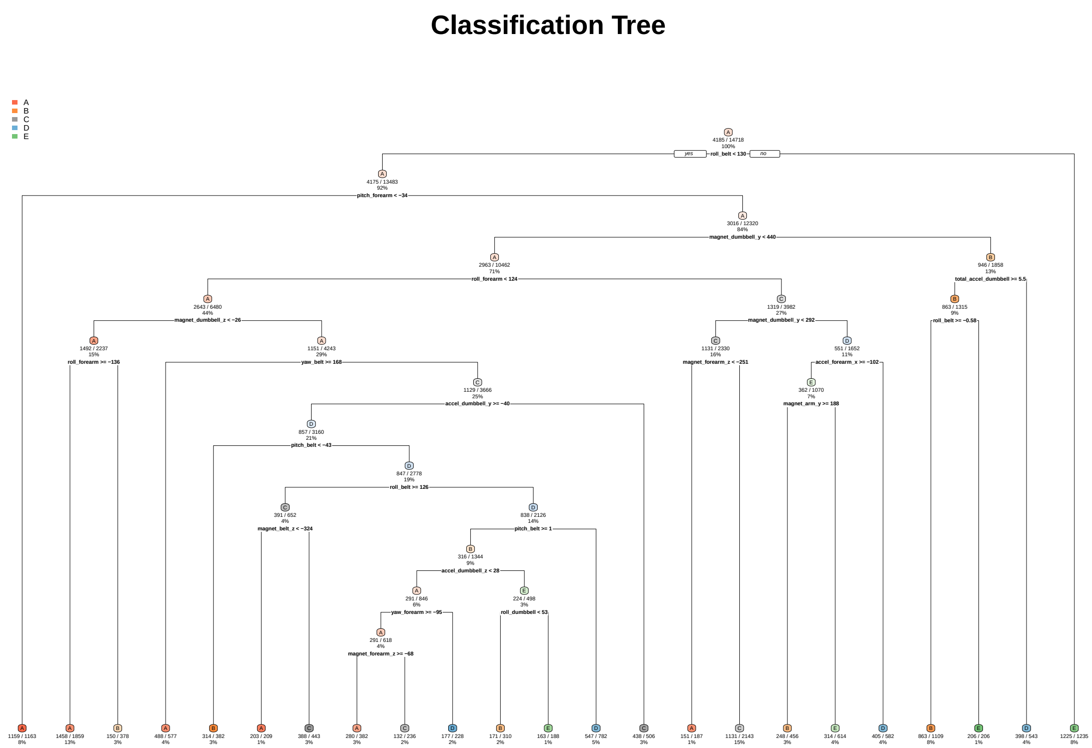
From the graph above, we can see that each level frequency is within the same order of magnitude of each other. Level A is the most frequent with more than 4000 occurrences while level D is the least frequent with about 2500 occurrences.

First prediction model: Using Decision Tree

```r
model1 <- rpart(classe ~ ., data=subTraining, method="class")

# Predicting:
prediction1 <- predict(model1, subTesting, type = "class")
```

```r
# Plot of the Decision Tree
rpart.plot(model1, main="Classification Tree", extra=102, under=TRUE, faclen=0)
```



Test results on our subTesting data set:

```r
confusionMatrix(prediction1, subTesting$classe)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1235  157   16   50   20
##          B   55  568   73   80  102
##          C   44  125  690  118  116
##          D   41   64   50  508   38
##          E   20   35   26   48  625
##
## Overall Statistics
##
##                Accuracy : 0.7394
##                  95% CI : (0.7269, 0.7516)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
```

```
##                  Kappa : 0.6697
##  Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.8853   0.5985   0.8070   0.6318   0.6937
## Specificity            0.9307   0.9216   0.9005   0.9529   0.9678
## Pos Pred Value         0.8356   0.6469   0.6313   0.7247   0.8289
## Neg Pred Value         0.9533   0.9054   0.9567   0.9296   0.9335
## Prevalence             0.2845   0.1935   0.1743   0.1639   0.1837
## Detection Rate         0.2518   0.1158   0.1407   0.1036   0.1274
## Detection Prevalence   0.3014   0.1790   0.2229   0.1429   0.1538
## Balanced Accuracy      0.9080   0.7601   0.8537   0.7924   0.8307
```

Second prediction model: Using Random Forest

```
model2 <- randomForest(classe ~. , data=subTraining, method="class")

# Predicting:
prediction2 <- predict(model2, subTesting, type = "class")

# Test results on subTesting data set:
confusionMatrix(prediction2, subTesting$classe)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1394    3    0    0    0
##          B    1  944   10    0    0
##          C    0    2  843    6    0
##          D    0    0    2  798    0
##          E    0    0    0    0  901
##
## Overall Statistics
##
##                Accuracy : 0.9951
##                  95% CI : (0.9927, 0.9969)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9938
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9993   0.9947   0.9860   0.9925   1.0000
## Specificity            0.9991   0.9972   0.9980   0.9995   1.0000
## Pos Pred Value         0.9979   0.9885   0.9906   0.9975   1.0000
## Neg Pred Value         0.9997   0.9987   0.9970   0.9985   1.0000
```

```
## Prevalence             0.2845   0.1935   0.1743   0.1639   0.1837
## Detection Rate         0.2843   0.1925   0.1719   0.1627   0.1837
## Detection Prevalence   0.2849   0.1947   0.1735   0.1631   0.1837
## Balanced Accuracy      0.9992   0.9960   0.9920   0.9960   1.0000
```

Decision

As expected, Random Forest algorithm performed better than Decision Trees. Accuracy for Random Forest model was 0.995 (95% CI: (0.993, 0.997)) compared to 0.739 (95% CI: (0.727, 0.752)) for Decision Tree model. The random Forest model is choosen. The accuracy of the model is 0.995. The expected out-of-sample error is estimated at 0.005, or 0.5%. The expected out-of-sample error is calculated as 1 - accuracy for predictions made against the cross-validation set. Our Test data set comprises 20 cases. With an accuracy above 99% on our cross-validation data, we can expect that very few, or none, of the test samples will be missclassified.

Submission

```r
# predict outcome levels on the original Testing data set using Random Forest algorithm
predictfinal <- predict(model2, testingset, type="class")
predictfinal
```

```
##  1  2  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
```

```r
# Write files for submission
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(predictfinal)
```

References

Velloso, Eduardo, Andreas Bulling, Hans Gellersen, Wallace Ugulino, and Hugo Fuks. 2013. "Qualitative Activity Recognition of Weight Lifting Exercises." In *Proceedings of the 4th Augmented Human International Conference*, 116–23. AH '13. New York, NY, USA: ACM. doi:10.1145/2459236.2459256.