Machine Learning Course Project Writeup

- Gokul Shah 2/3/2021

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. 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 (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 (https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv)]

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

What you should submit

The goal of your project is to predict the manner in which they did the exercise. This is the “classe” variable in the training set. You may use any of the other variables to predict with. You should create a report describing how you built your model, how you used cross validation, what you think the expected out of sample error is, and why you made the choices you did. You will also use your prediction model to predict 20 different test cases.

Your submission should consist of a link to a Github repo with your R markdown and compiled HTML file describing your analysis. Please constrain the text of the writeup to < 2000 words and the number of figures to be less than 5. It will make it easier for the graders if you submit a repo with a gh-pages branch so the HTML page can be viewed online (and you always want to make it easy on graders :-). You should also apply your machine learning algorithm to the 20 test cases available in the test data above. Please submit your predictions in appropriate format to the programming assignment for automated grading. See the programming assignment for additional details.

Approach:

Our outcome variable is classe, a factor variable. For this data set, “participants were asked to perform one set of 10 repetitions of the Unilateral Dumbbell Biceps Curl in 5 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) - throwing the hips to the front (Class E)

Two models will be tested using decision tree and random forest. The model with the highest accuracy will be chosen as our final model.

Cross-validation

Cross-validation will be performed by subsampling our training data set randomly without replacement into 2 subsamples: TrainTrainingSet data (75% of the original Training data set) and TestTrainingSet data (25%). Our models will be fitted on the TrainTrainingSet data set, and tested on the TestTrainingSet data. Once the most accurate model is choosen, it will be tested on the original Testing data set.

Expected out-of-sample error

The expected out-of-sample error will correspond to the quantity: 1-accuracy in the cross-validation data. Accuracy is the proportion of correct classified observation over the total sample in the TestTrainingSet data set. Expected accuracy is the expected accuracy in the out-of-sample data set (i.e. original testing data set). Thus, the expected value of the out-of-sample error will correspond to the expected number of missclassified observations/total observations in the Test data set, which is the quantity: 1-accuracy found from the cross-validation data set.

Our outcome variable "classe" is a factor variable. We split the Training dataset into TrainTrainingSet and TestTrainingSet datasets.

Install packages and load the required libraries

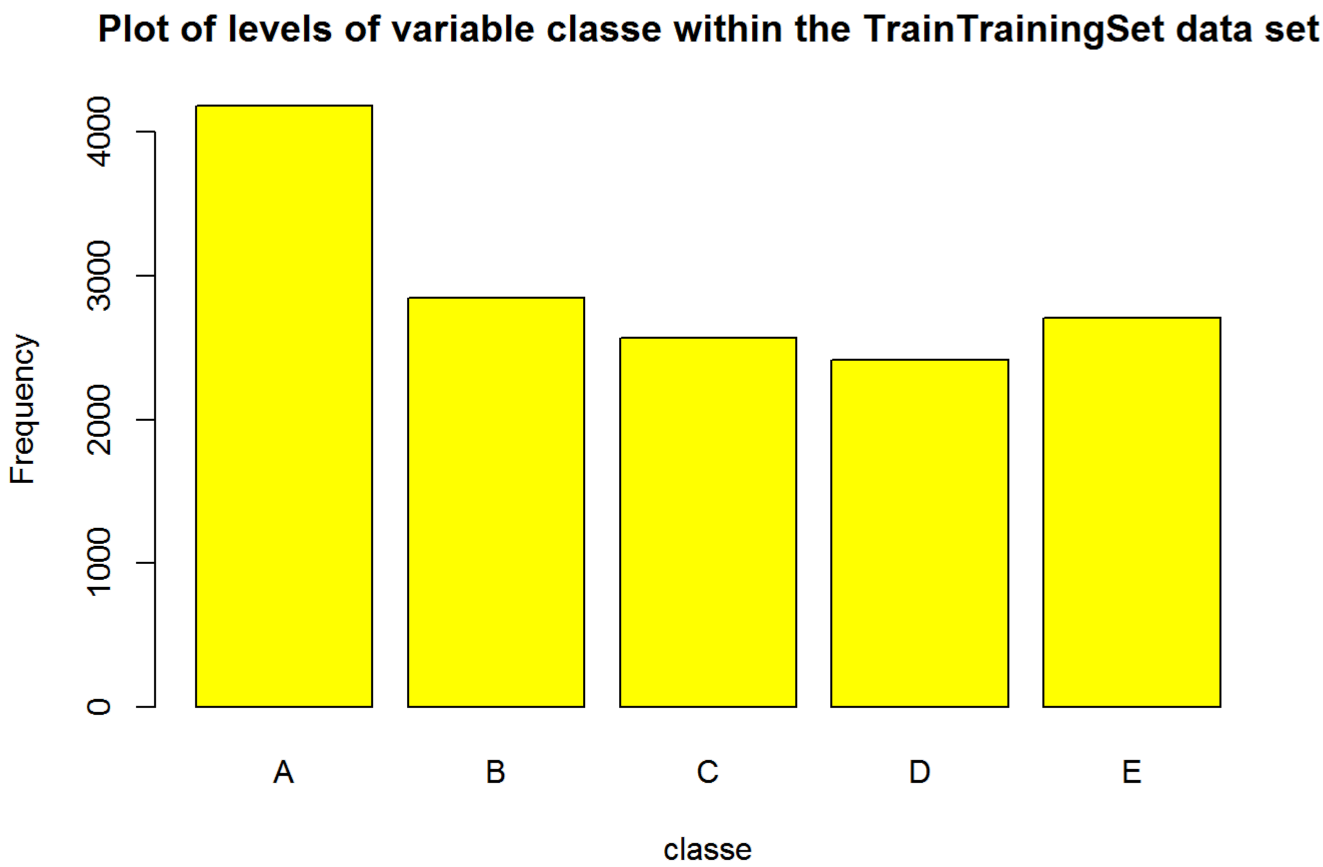
```
# install.packages("caret"); install.packages("randomForest"); install.packages("rpart");
library(lattice); library(ggplot2); library(caret); library(randomForest); library(rpart); library(rpart.plo
t);
```

```
## Warning: package 'lattice' was built under R version 3.1.1
## Warning: package 'ggplot2' was built under R version 3.1.1
## Warning: package 'caret' was built under R version 3.1.2
## Warning: package 'randomForest' was built under R version 3.1.2
```

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

```
## Warning: package 'rpart.plot' was built under R version 3.1.2
```

```
set.seed(1234)

# data load and clean up
trainingset <- read.csv("pml-training.csv", na.strings=c("NA","#DIV/0!", ""))
testingset <- read.csv("pml-testing.csv", na.strings=c("NA","#DIV/0!", ""))

# Perform exploratory analysis -
# dim(trainingset); dim(testingset); summary(trainingset); summary(testingset); str(trainingset); str(testin
gset); head(trainingset); head(testingset);

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

# Delete variables are irrelevant to our current project: user_name, raw_timestamp_part_1, raw_timestamp_par
t_,2 cvtd_timestamp, new_window, and  num_window (columns 1 to 7).
trainingset   <-trainingset[,-c(1:7)]
testingset <-testingset[,-c(1:7)]

# partition the data so that 75% of the training dataset into training and the remaining 25% to testing
traintrainset <- createDataPartition(y=trainingset$classe, p=0.75, list=FALSE)
TrainTrainingSet <- trainingset[traintrainset, ]
TestTrainingSet <- trainingset[-traintrainset, ]

# 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 TrainTrainingSet data set and # compare one another.

plot(TrainTrainingSet$classe, col="yellow", main="Plot of levels of variable classe within the TrainTraining
Set data set", xlab="classe", ylab="Frequency")
```

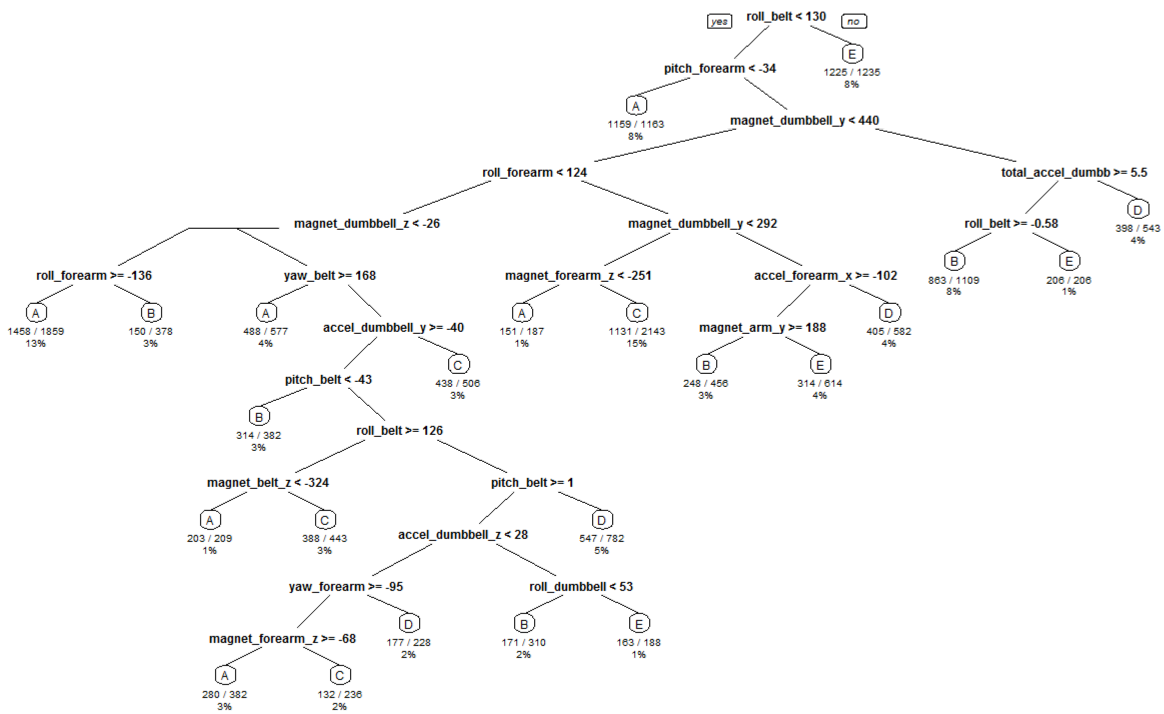


Based on the graph above, we can see that each level frequency is within the same order of magnitude of each other. Level A is the most frequent while level D is the least frequent.

Prediction model 1: Decision Tree

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

prediction1 <- predict(model1, TestTrainingSet, type = "class")

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

Classification Tree




```
# Test results on our TestTrainingSet data set:
confusionMatrix(prediction1, TestTrainingSet$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 : 0.739
##                  95% CI : (0.727, 0.752)
##     No Information Rate : 0.284
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.67
##  Mcnemar's Test P-Value : <2e-16
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity             0.885    0.599    0.807    0.632    0.694
## Specificity             0.931    0.922    0.900    0.953    0.968
## Pos Pred Value          0.836    0.647    0.631    0.725    0.829
## Neg Pred Value          0.953    0.905    0.957    0.930    0.933
## Prevalence              0.284    0.194    0.174    0.164    0.184
## Detection Rate          0.252    0.116    0.141    0.104    0.127
## Detection Prevalence    0.301    0.179    0.223    0.143    0.154
## Balanced Accuracy       0.908    0.760    0.854    0.792    0.831
```

Prediction model 2: Random Forest

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

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

# Test results on TestTrainingSet data set:
confusionMatrix(prediction2, TestTrainingSet$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 : 0.995
##                  95% CI : (0.993, 0.997)
##     No Information Rate : 0.284
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.994
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity             0.999    0.995    0.986    0.993    1.000
## Specificity             0.999    0.997    0.998    1.000    1.000
## Pos Pred Value          0.998    0.988    0.991    0.997    1.000
## Neg Pred Value          1.000    0.999    0.997    0.999    1.000
## Prevalence              0.284    0.194    0.174    0.164    0.184
## Detection Rate          0.284    0.192    0.172    0.163    0.184
## Detection Prevalence    0.285    0.195    0.174    0.163    0.184
## Balanced Accuracy       0.999    0.996    0.992    0.996    1.000
```

Decision on which Prediction Model to Use:

Random Forest algorithm performed better than Decision Trees. Accuracy for Random Forest model was 0.995 (95% CI: (0.993, 0.997)) compared to Decision Tree model with 0.739 (95% CI: (0.727, 0.752)). The Random Forests model is choosen. The expected out-of-sample error is estimated at 0.005, or 0.5%.

Submission

Here is the final outcome based on the Prediction Model 2 (Random Forest) applied against the Testing dataset

```
# 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
```