Background and Problem Statement

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. The goal for this project is to use data from accelerometers on the belt, forearm, arm, and dumbell of 6 participants to predict the manner in which they did the exercise. Participants were asked to perform barbell lifts correctly and incorrectly in 5 different ways. More information is available here: [http://groupware.les.inf.puc-rio.br/har] (see the section on the Weight Lifting Exercise Dataset).

Data

The training data subset for this project is available here: [https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv]

The test data subset is available here: [https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv]

Data Source: [http://groupware.les.inf.puc-rio.br/har].

Goal

The goal of this project is to find the model that more accurately predicts the “classe” variable in the training set using the rest of the variables available in the dataset. t

Preliminary Work

Reproduceability

An overall pseudo-random number generator seed was set at 876. In order for the results below to be reproduced, the same seed should be used. Required libraries will need to be installed prior use (you can use “install.packages(”nameofpackage“)”.

```
#Preliminaries
# set working directory
directory <- "C:\\Users\\Constantina\\Google Drive\\Data Science and Business Analytics\\coursera\\Data
setwd(directory)
set.seed(876)
```

How the model was built

The outcome variable is **classe**, a factor variable with 5 levels. 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)

Class A corresponds to the specified execution of the exercise, while the other 4 classes correspond to common mistakes." [1] Prediction evaluations will be based on maximizing the accuracy and minimizing the out-of-sample error. All other available variables after cleaning will be used for prediction. Two models will be tested using decision tree and random forest algorithms. The model with the highest accuracy will be chosen as the final model.

Approach

1. Load the data set and briefly learn the characteristics of the data
2. Use cross-validation method to built a valid model; 70% of the original data is used for model building (training data) while the rest of 30% of the data is used for testing (testing data)
3. Since the number of variables in the training data is too large, clean the data by a) excluding variables which apparently cannot be explanatory variables, and b) reducing variables with little information.
4. Apply Principle component Analysis (PCA) to reduce the number of variables
5. Apply random forest method to build a model
6. Check the model with the testing data set
7. Apply the model to estimate classes of 20 observations

Loading data

```
#download & load data
#trainUrl <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
#testUrl <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"
trainUrl <- "pml-training.csv"
testUrl <- "pml-testing.csv"
training <- read.csv(trainUrl, na.strings=c("NA","#DIV/0!",""))
testing <- read.csv(testUrl, na.strings=c("NA","#DIV/0!",""))

#required libraries
library(caret)
```

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

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

```
#library(randomForest)
#library(rpart)
#library(rpart.plot)
#library(RColorBrewer)
#library(rattle)
```

Cross-validation

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

```
in_train <- createDataPartition(y=training$classe, p=0.75, list=FALSE)
my_training <- training[in_train, ]; my_testing <- training[-in_train, ]
dim(my_training); dim(my_testing)
```

```
## [1] 14718   160
```

```
## [1] 4904  160
```

Cleaning the training data

The following transformations were used to clean the data:

Transformation 1: Cleaning near-zero-variance variables.

```
my_NZV <- nearZeroVar(my_training, saveMetrics=TRUE)
NZV_vars <- names(my_training) %in% c("new_window", "kurtosis_roll_belt", "kurtosis_picth_belt",
"kurtosis_yaw_belt", "skewness_roll_belt", "skewness_roll_belt.1", "skewness_yaw_belt",
"max_yaw_belt", "min_yaw_belt", "amplitude_yaw_belt", "avg_roll_arm", "stddev_roll_arm",
"var_roll_arm", "avg_pitch_arm", "stddev_pitch_arm", "var_pitch_arm", "avg_yaw_arm",
"stddev_yaw_arm", "var_yaw_arm", "kurtosis_roll_arm", "kurtosis_picth_arm",
"kurtosis_yaw_arm", "skewness_roll_arm", "skewness_pitch_arm", "skewness_yaw_arm",
"max_roll_arm", "min_roll_arm", "min_pitch_arm", "amplitude_roll_arm", "amplitude_pitch_arm",
"kurtosis_roll_dumbbell", "kurtosis_picth_dumbbell", "kurtosis_yaw_dumbbell", "skewness_roll_dumbbell",
"skewness_pitch_dumbbell", "skewness_yaw_dumbbell", "max_yaw_dumbbell", "min_yaw_dumbbell",
"amplitude_yaw_dumbbell", "kurtosis_roll_forearm", "kurtosis_picth_forearm", "kurtosis_yaw_forearm",
"skewness_roll_forearm", "skewness_pitch_forearm", "skewness_yaw_forearm", "max_roll_forearm",
"max_yaw_forearm", "min_roll_forearm", "min_yaw_forearm", "amplitude_roll_forearm",
"amplitude_yaw_forearm", "avg_roll_forearm", "stddev_roll_forearm", "var_roll_forearm",
"avg_pitch_forearm", "stddev_pitch_forearm", "var_pitch_forearm", "avg_yaw_forearm",
"stddev_yaw_forearm", "var_yaw_forearm")
my_training <- my_training[!NZV_vars]

dim(my_training)
```

```
## [1] 14718   100
```

Transformation 2: Removing first ID variable so that it does not interfer with ML Algorithms:

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

Transformation 3: Variables containing more than 60% of NA's are left out:

```
training_V3 <- my_training #creating another subset to iterate in loop
for(i in 1:length(my_training)) { #for every column in the training dataset
        if( sum( is.na( my_training[, i] ) ) /nrow(my_training) >= .6 ) { #if n?? NAs > 60% of total ob
        for(j in 1:length(training_V3)) {
            if( length( grep(names(my_training[i]), names(training_V3)[j]) ) ==1)  { #if the columns ar
                training_V3 <- training_V3[ , -j] #Remove that column
            }
        }
```

```r
    }
}
#To check the new N?? of observations
dim(training_V3)
```

```
## [1] 14718    58
```

```r
#Setting back to our set:
my_training <- training_V3
rm(training_V3)
```

Transformations for my_testing and testing data sets.

```r
clean1 <- colnames(my_training)
clean2 <- colnames(my_training[, -58]) #already with classe column removed
my_testing <- my_testing[clean1]
testing <- testing[clean2]

#To check the new N?? of observations
dim(my_testing)
```

```
## [1] 4904   58
```

```r
dim(testing)
```

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

coercion of data

```r
for (i in 1:length(testing) ) {
        for(j in 1:length(my_training)) {
        if( length( grep(names(my_training[i]), names(testing)[j]) ) ==1)  {
            class(testing[j]) <- class(my_training[i])
        }
    }
}
#And to make sure Coertion really worked:
testing <- rbind(my_training[2, -58] , testing) #note row 2 does not mean anything, this will be remove
testing <- testing[-1,]
```

Using ML algorithms for prediction: Decision Tree

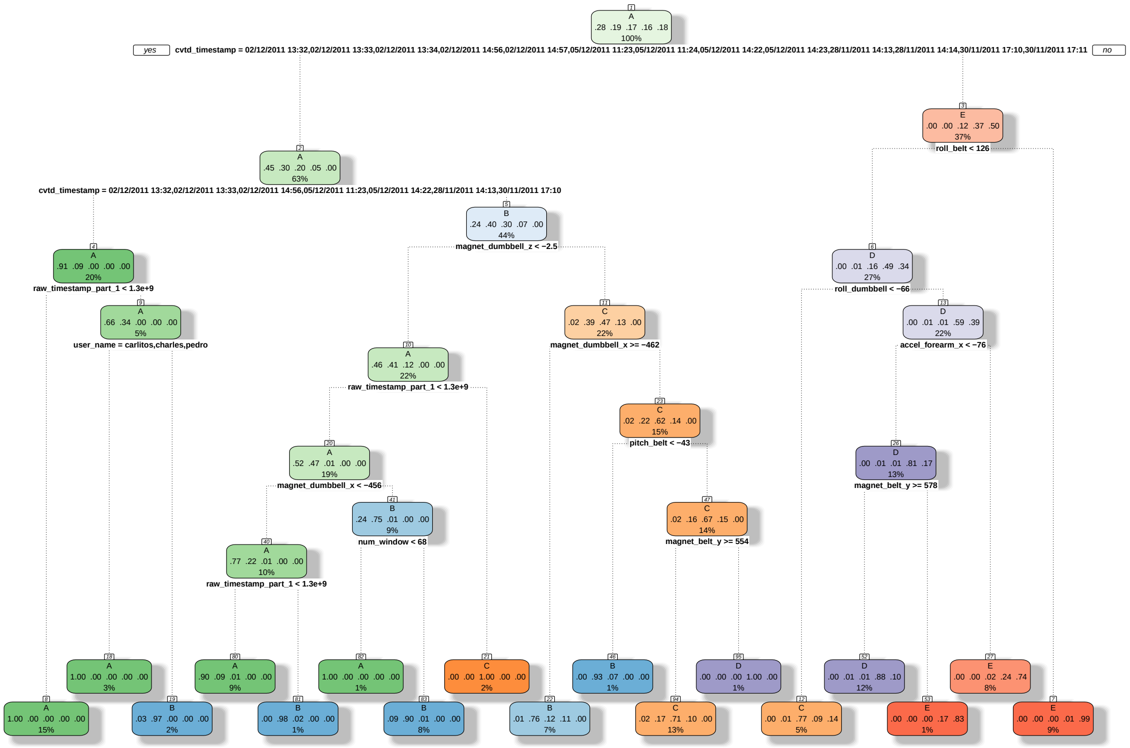
```r
library(rpart)
library(rattle)
```

```
## Rattle: A free graphical interface for data mining with R.
## Version 4.1.0 Copyright (c) 2006-2015 Togaware Pty Ltd.
## Type 'rattle()' to shake, rattle, and roll your data.
```

```
mod_Fit_A1 <- rpart(classe ~ ., data=my_training, method="class")
```

Note: Viewing the decision tree.

```
fancyRpartPlot(mod_Fit_A1)
```



Rattle 2016−Oct−01 20:24:16 Constantina

Predicting:

```
predictions_A1 <- predict(mod_Fit_A1, my_testing, type = "class")
```

Using confusion Matrix to test results:

```
confusionMatrix(predictions_A1, my_testing$classe)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1348   41    4    1    0
##          B   35  783   51   41    0
##          C   12  120  783   84   31
##          D    0    5   11  550   48
##          E    0    0    6  128  822
##
```

```
## Overall Statistics
##
##                Accuracy : 0.874
##                  95% CI : (0.8644, 0.8831)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.8405
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9663   0.8251   0.9158   0.6841   0.9123
## Specificity            0.9869   0.9679   0.9390   0.9844   0.9665
## Pos Pred Value         0.9670   0.8604   0.7602   0.8958   0.8598
## Neg Pred Value         0.9866   0.9584   0.9814   0.9408   0.9800
## Prevalence             0.2845   0.1935   0.1743   0.1639   0.1837
## Detection Rate         0.2749   0.1597   0.1597   0.1122   0.1676
## Detection Prevalence   0.2843   0.1856   0.2100   0.1252   0.1949
## Balanced Accuracy      0.9766   0.8965   0.9274   0.8342   0.9394
```

Using ML algorithms for prediction: Random Forests

```
library(randomForest)
```

```
## randomForest 4.6-12
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

```
##
## Attaching package: 'randomForest'
```

```
## The following object is masked from 'package:ggplot2':
##
##     margin
```

```
mod_Fit_B1 <- randomForest(classe ~. , data=my_training)
```

Predicting in-sample error:

```
predictions_B1 <- predict(mod_Fit_B1, my_testing, type = "class")
```

Using confusion Matrix to test results:

```
confusionMatrix(predictions_B1, my_testing$classe)
```

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

```
##           Reference
## Prediction    A    B    C    D    E
##          A 1395    1    0    0    0
##          B    0  948    0    0    0
##          C    0    0  855    1    0
##          D    0    0    0  803    0
##          E    0    0    0    0  901
##
## Overall Statistics
##
##                Accuracy : 0.9996
##                  95% CI : (0.9985, 1)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9995
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   0.9989   1.0000   0.9988   1.0000
## Specificity            0.9997   1.0000   0.9998   1.0000   1.0000
## Pos Pred Value         0.9993   1.0000   0.9988   1.0000   1.0000
## Neg Pred Value         1.0000   0.9997   1.0000   0.9998   1.0000
## Prevalence             0.2845   0.1935   0.1743   0.1639   0.1837
## Detection Rate         0.2845   0.1933   0.1743   0.1637   0.1837
## Detection Prevalence   0.2847   0.1933   0.1746   0.1637   0.1837
## Balanced Accuracy      0.9999   0.9995   0.9999   0.9994   1.0000
```

Generating Files to submit as answers for the Assignment:

Finally, using the provided Test Set out-of-sample error.

For Random Forests we use the following formula, which yielded a much better prediction in in-sample:

```
predictions_B2 <- predict(mod_Fit_B1, testing, type = "class")
```

Function to generate files with predictions to submit for assignment

```
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(predictions_B2)
```