Practical Machine Learning Course Project

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Overview

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 (see the section on the Weight Lifting Exercise Dataset).

Exploratory Data Analysis

Data Source and Discussion

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.

"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. Participants were supervised by an experienced weight lifter to make sure the execution complied to the manner they were supposed to simulate. The exercises were performed by six male participants aged between 20-28 years, with little weight lifting experience. We made sure that all participants could easily simulate the mistakes in a safe and controlled manner by using a relatively light dumbbell (1.25kg)." [1]

Preparation of the R Environment

[1] Velloso, E.; Bulling, A.; Gellersen, H.; Ugulino, W.; Fuks, H. "Qualitative Activity Recognition of Weight Lifting Exercises. Proceedings of 4th International Conference in Cooperation with SIGCHI (Augmented Human '13)". Stuttgart, Germany: ACM SIGCHI, 2013.

```r
rm(list=ls())                  # free up memory for the download of the data sets
setwd("C:/Users/jordan.becker/Desktop/GD/2016_Research/GitHub")
library(knitr)
```

```
## Warning: package 'knitr' was built under R version 3.3.2
```

```r
library(caret)
```

```
## Warning: package 'caret' was built under R version 3.3.2

## Loading required package: lattice

## Loading required package: ggplot2

## Warning: package 'ggplot2' was built under R version 3.3.2
```

```r
library(rpart)
```

```
## Warning: package 'rpart' was built under R version 3.3.2
```

```r
library(rpart.plot)
```

```
## Warning: package 'rpart.plot' was built under R version 3.3.2
```

```r
library(rattle)
```

```
## Warning: package 'rattle' was built under R version 3.3.2

## 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.
```

```r
library(randomForest)
```

```
## Warning: package 'randomForest' was built under R version 3.3.2

## 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
```

```r
library(corrplot)
```

```
## Warning: package 'corrplot' was built under R version 3.3.2
```

```r
set.seed(12345)
```

Load and Clean Data

```r
# set the URL for the download
UrlTrain <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
UrlTest  <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"

# download the datasets
```

```r
training <- read.csv(url(UrlTrain))
testing  <- read.csv(url(UrlTest))

# create a partition with the training dataset
inTrain  <- createDataPartition(training$classe, p=0.7, list=FALSE)
TrainSet <- training[inTrain, ]
TestSet  <- training[-inTrain, ]
dim(TrainSet)
```

```
## [1] 13737   160
```

```r
dim(TestSet)
```

```
## [1] 5885  160
```

Both the training and the test set have 160 variables with many missing observations that can be cleaned, along with variables that don't vary and the ID variables.

```r
# remove variables with Nearly Zero Variance
NZV <- nearZeroVar(TrainSet)
TrainSet <- TrainSet[, -NZV]
TestSet  <- TestSet[, -NZV]
dim(TrainSet)
```

```
## [1] 13737   106
```

```r
dim(TestSet)
```

```
## [1] 5885  106
```

```r
# remove variables with mostly missing data
AllNA    <- sapply(TrainSet, function(x) mean(is.na(x))) > 0.95
TrainSet <- TrainSet[, AllNA==FALSE]
TestSet  <- TestSet[, AllNA==FALSE]
dim(TrainSet)
```

```
## [1] 13737    59
```

```r
dim(TestSet)
```

```
## [1] 5885   59
```

```r
# remove identification only variables (columns 1 to 5)
TrainSet <- TrainSet[, -(1:5)]
TestSet  <- TestSet[, -(1:5)]
dim(TrainSet)
```

```
## [1] 13737    54
```

```r
dim(TestSet)
```

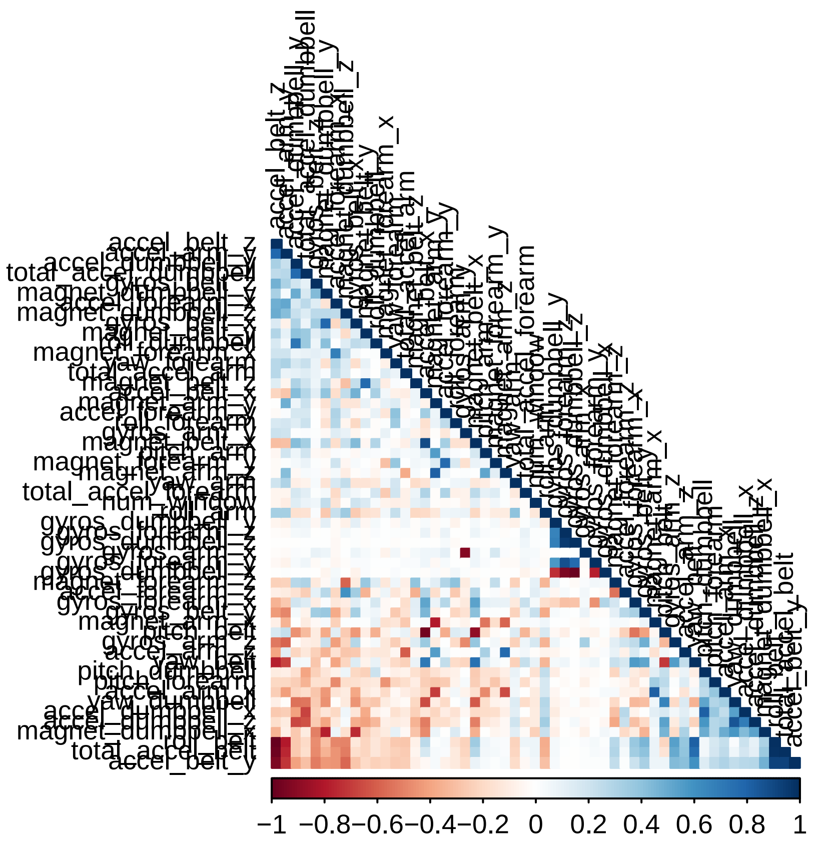
```
## [1] 5885   54
```

We are now down to 54 variables for analysis

Correlation Analysis

Some pairwise correlations before moving to more detailed analysis.

```r
corMatrix <- cor(TrainSet[, -54])
corrplot(corMatrix, order = "FPC", method = "color", type = "lower",
         tl.cex = 0.8, tl.col = rgb(0, 0, 0))
```



Darker colors indicate higher correlation coefficients between the two variables in the matrix.

Developing the Prediction Model

I test three methods for the regression analysis, and use a confusion matrix to plot the accuracy of each model. I then use the most accurate method on the Test Set.

Method 1: Random Forest

```r
# model fit
set.seed(12345)
controlRF <- trainControl(method="cv", number=3, verboseIter=FALSE)
modFitRandForest <- train(classe ~ ., data=TrainSet, method="rf",
                          trControl=controlRF)
modFitRandForest$finalModel
```

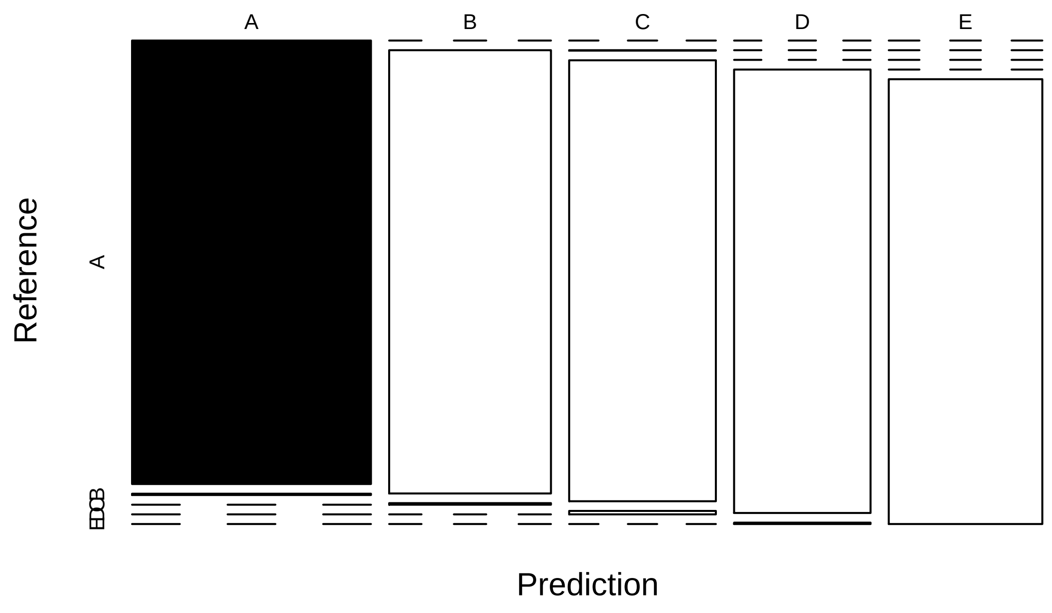
```
##
## Call:
##  randomForest(x = x, y = y, mtry = param$mtry)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 27
##
##         OOB estimate of  error rate: 0.2%
## Confusion matrix:
##      A    B    C    D    E  class.error
## A 3904    1    0    0    1 0.0005120328
## B    5 2652    1    0    0 0.0022573363
## C    0    5 2390    1    0 0.0025041736
## D    0    0    7 2245    0 0.0031083481
## E    0    1    0    5 2519 0.0023762376
```

```
# prediction on Test dataset
predictRandForest <- predict(modFitRandForest, newdata=TestSet)
confMatRandForest <- confusionMatrix(predictRandForest, TestSet$classe)
confMatRandForest
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1674    5    0    0    0
##          B    0 1133    4    0    0
##          C    0    1 1022    8    0
##          D    0    0    0  956    3
##          E    0    0    0    0 1079
##
## Overall Statistics
##
##                Accuracy : 0.9964
##                  95% CI : (0.9946, 0.9978)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9955
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   0.9947   0.9961   0.9917   0.9972
## Specificity            0.9988   0.9992   0.9981   0.9994   1.0000
## Pos Pred Value         0.9970   0.9965   0.9913   0.9969   1.0000
## Neg Pred Value         1.0000   0.9987   0.9992   0.9984   0.9994
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2845   0.1925   0.1737   0.1624   0.1833
## Detection Prevalence   0.2853   0.1932   0.1752   0.1630   0.1833
## Balanced Accuracy      0.9994   0.9969   0.9971   0.9955   0.9986
```

```
# plot matrix results
plot(confMatRandForest$table, col = confMatRandForest$byClass,
     main = paste("Random Forest - Accuracy =",
                  round(confMatRandForest$overall['Accuracy'], 4)))
```

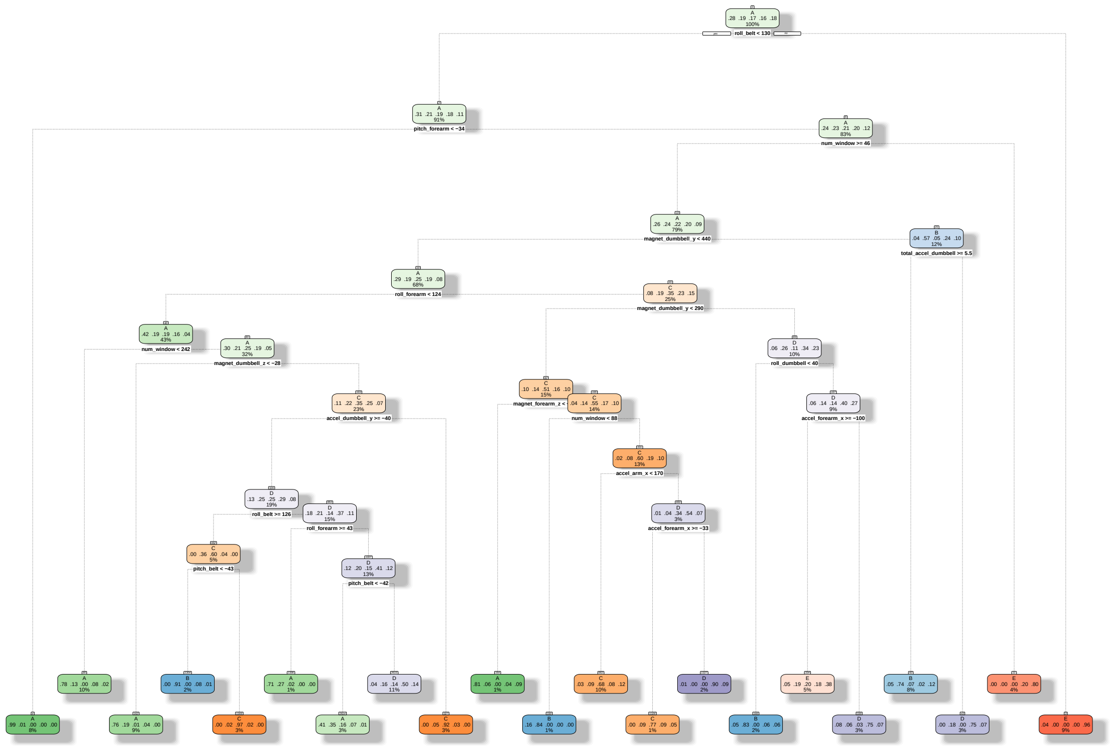
Random Forest − Accuracy = 0.9964



Method 2: Decision Trees

```r
# model fit
set.seed(12345)
modFitDecTree <- rpart(classe ~ ., data=TrainSet, method="class")
fancyRpartPlot(modFitDecTree)
```

```
## Warning: labs do not fit even at cex 0.15, there may be some overplotting
```



Rattle 2017−Mar−05 12:55:17 jordan.becker

```
# prediction on Test dataset
predictDecTree <- predict(modFitDecTree, newdata=TestSet, type="class")
confMatDecTree <- confusionMatrix(predictDecTree, TestSet$classe)
confMatDecTree
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1530  269   51   79   16
##          B   35  575   31   25   68
##          C   17   73  743   68   84
##          D   39  146  130  702  128
##          E   53   76   71   90  786
##
## Overall Statistics
##
##                Accuracy : 0.7368
##                  95% CI : (0.7253, 0.748)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.6656
##  Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
##
```

```
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9140  0.50483   0.7242   0.7282   0.7264
## Specificity            0.9014  0.96650   0.9502   0.9100   0.9396
## Pos Pred Value         0.7866  0.78338   0.7543   0.6131   0.7305
## Neg Pred Value         0.9635  0.89051   0.9422   0.9447   0.9384
## Prevalence             0.2845  0.19354   0.1743   0.1638   0.1839
## Detection Rate         0.2600  0.09771   0.1263   0.1193   0.1336
## Detection Prevalence   0.3305  0.12472   0.1674   0.1946   0.1828
## Balanced Accuracy      0.9077  0.73566   0.8372   0.8191   0.8330
```

Method 3: Generalized Boosted Model

```r
# model fit
set.seed(12345)
controlGBM <- trainControl(method = "repeatedcv", number = 5, repeats = 1)
modFitGBM  <- train(classe ~ ., data=TrainSet, method = "gbm",
                    trControl = controlGBM, verbose = FALSE)
```

```
## Loading required package: gbm

## Warning: package 'gbm' was built under R version 3.3.2

## Loading required package: survival

## Warning: package 'survival' was built under R version 3.3.2

##
## Attaching package: 'survival'

## The following object is masked from 'package:caret':
##
##     cluster

## Loading required package: splines

## Loading required package: parallel

## Loaded gbm 2.1.1

## Loading required package: plyr
```

```r
modFitGBM$finalModel
```

```
## A gradient boosted model with multinomial loss function.
## 150 iterations were performed.
## There were 53 predictors of which 43 had non-zero influence.
```

```r
# prediction on Test dataset
predictGBM <- predict(modFitGBM, newdata=TestSet)
confMatGBM <- confusionMatrix(predictGBM, TestSet$classe)
confMatGBM
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1670    9    0    3    0
##          B    2 1117   20    2    1
##          C    0   11 1004   14    3
##          D    1    2    2  944   11
##          E    1    0    0    1 1067
## 
## Overall Statistics
## 
##                Accuracy : 0.9859          
##                  95% CI : (0.9825, 0.9888)
##     No Information Rate : 0.2845          
##     P-Value [Acc > NIR] : < 2.2e-16       
## 
##                   Kappa : 0.9822          
##  Mcnemar's Test P-Value : NA              
## 
## Statistics by Class:
## 
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9976   0.9807   0.9786   0.9793   0.9861
## Specificity            0.9972   0.9947   0.9942   0.9967   0.9996
## Pos Pred Value         0.9929   0.9781   0.9729   0.9833   0.9981
## Neg Pred Value         0.9990   0.9954   0.9955   0.9959   0.9969
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2838   0.1898   0.1706   0.1604   0.1813
## Detection Prevalence   0.2858   0.1941   0.1754   0.1631   0.1816
## Balanced Accuracy      0.9974   0.9877   0.9864   0.9880   0.9929
```

Testing the Data with the Random Forest Model

The Random Forest Model has a better fit (0.9963) than the Decision Tree Model (0.7368) or the GBM (0.9839). So I will use it to predict the results:

```
predictTEST <- predict(modFitRandForest, newdata=testing)
predictTEST
```

```
##  [1] 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
```