Prediction Assignment

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Introduction

Data collection through self-monitoring and self-sensing combines wearable sensors (e.g.Electroencephalography, Electrocardiography) and wearable computing (smartwatchs, heart rate monitors, etc.) See Quantified self. Using wereable computers like known fitness accessories is now possible to collect a large amount of data about fitness personal activity in an inexpensively way. This trackers devices are part of a "life logging" movement, and a general characteristic of the information collected is that is known how much a particular activity was did it, but rarely quantified how well they did it.
In this project, the goal is 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: http://groupware.les.inf.puc-rio.br/har (see the section on the Weight Lifting Exercise Dataset).

Executive Resume

The description of the assignment contains the following information on the dataset:
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.
The goal is
to predict the manner in which they did the exercise.

Building the model

Reproducibility

Preparing the data and R packages

The following Libraries were used for this project, so you should install and load them in your own working environment.

```
library(caret)
```

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

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

```
library(corrplot)
library(RColorBrewer)
```

```
getRversion()
```

```
## [1] '3.4.0'
```

I choose randomForest (as a supervised learning algorithm), because of their known utility in classification problems, and gives an acceptable level of performance.

Getting Data

```
trainUrl <-"https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
testUrl <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"
trainFile <- "/Users/carlosbarco/R/pml-training.csv"
testFile  <- "/Users/carlosbarco/R/pml-testing.csv"
if (!file.exists("./data")) {
  dir.create("./data")
}
if (!file.exists(trainFile)) {
  download.file(trainUrl, destfile = trainFile, method = "curl")
}
if (!file.exists(testFile)) {
  download.file(testUrl, destfile = testFile, method = "curl")
}
```

Reading Data

```
trainRaw <- read.csv(trainFile)
testRaw <- read.csv(testFile)
dim(trainRaw)
```

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

```
dim(testRaw)
```

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

```
rm(trainFile)
rm(testFile)
```

The amount of observations between training and test sets are very different, but contains the same number of variables (160). In our case, the "classe" variable is the one to predict.

Cleaning Data

Clean the Near Zero Variance Variables.

```
NZV <- nearZeroVar(trainRaw, saveMetrics = TRUE)
head(NZV, 20)
```

```
##                          freqRatio percentUnique zeroVar   nzv
## X                         1.000000  100.00000000   FALSE FALSE
## user_name                 1.100679    0.03057792   FALSE FALSE
```

```
## raw_timestamp_part_1     1.000000    4.26562022   FALSE FALSE
## raw_timestamp_part_2     1.000000   85.53154622   FALSE FALSE
## cvtd_timestamp           1.000668    0.10192641   FALSE FALSE
## new_window              47.330049    0.01019264   FALSE  TRUE
## num_window               1.000000    4.37264295   FALSE FALSE
## roll_belt                1.101904    6.77810621   FALSE FALSE
## pitch_belt               1.036082    9.37722964   FALSE FALSE
## yaw_belt                 1.058480    9.97349913   FALSE FALSE
## total_accel_belt         1.063160    0.14779329   FALSE FALSE
## kurtosis_roll_belt    1921.600000    2.02323922   FALSE  TRUE
## kurtosis_picth_belt    600.500000    1.61553358   FALSE  TRUE
## kurtosis_yaw_belt       47.330049    0.01019264   FALSE  TRUE
## skewness_roll_belt    2135.111111    2.01304658   FALSE  TRUE
## skewness_roll_belt.1   600.500000    1.72255631   FALSE  TRUE
## skewness_yaw_belt       47.330049    0.01019264   FALSE  TRUE
## max_roll_belt            1.000000    0.99378249   FALSE FALSE
## max_picth_belt           1.538462    0.11211905   FALSE FALSE
## max_yaw_belt           640.533333    0.34654979   FALSE  TRUE
```

```r
training01 <- trainRaw[, !NZV$nzv]
testing01 <- testRaw[, !NZV$nzv]
dim(training01)
```

```
## [1] 19622   100
```

```r
dim(testing01)
```

```
## [1]  20 100
```

```r
rm(trainRaw)
rm(testRaw)
rm(NZV)
```

Also, removing some columns of the dataset that do not contribute much to the accelerometer measurements.

```r
regex <- grepl("^X|timestamp|user_name", names(training01))
training <- training01[, !regex]
testing <- testing01[, !regex]
rm(regex)
rm(training01)
rm(testing01)
dim(training)
```

```
## [1] 19622    95
```

```r
dim(testing)
```

```
## [1] 20 95
```

removing columns that contain NA's.

```r
cond <- (colSums(is.na(training)) == 0)
training <- training[, cond]
testing <- testing[, cond]
rm(cond)
```

Now, the cleaned training data set contains:

```r
dim(training)
```

```
## [1] 19622    54
```

```r
#observations/variables
```

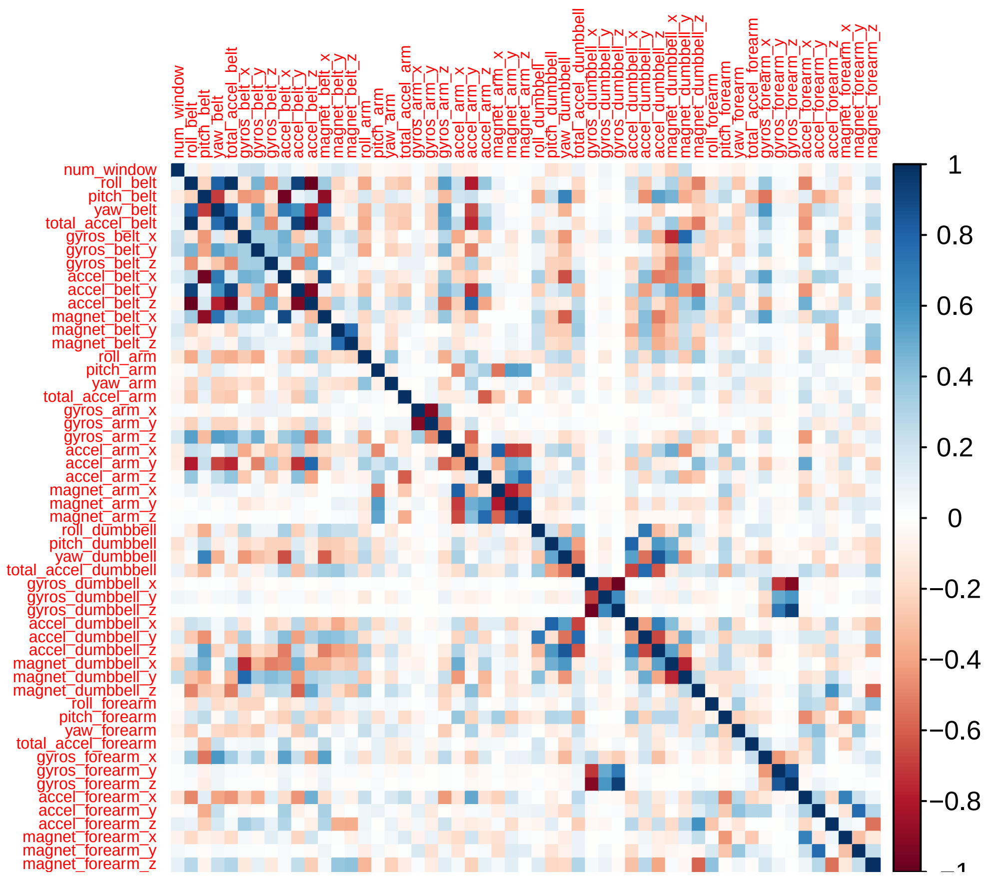
```r
dim(testing)
```

```
## [1] 20 54
```

```r
#observations/variables
```

Correlation Matrix of Columns in the Training Data set.

```r
corrplot(cor(training[, -length(names(training))]), method = "color", tl.cex = 0.5)
```



Partitioning Training Set

Was achieved by splitting the training data into a training set (70%) and a validation set (30%) using the following:

```r
set.seed(56789) # For reproducibile purpose
inTrain <- createDataPartition(training$classe, p = 0.70, list = FALSE)
validation <- training[-inTrain, ]
training <- training[inTrain, ]
rm(inTrain)
```

The training data set consist of

```r
dim(training)
```

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

The validation data set

```r
dim(validation)
```

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

and the Testing Data of

```r
dim(testing)
```

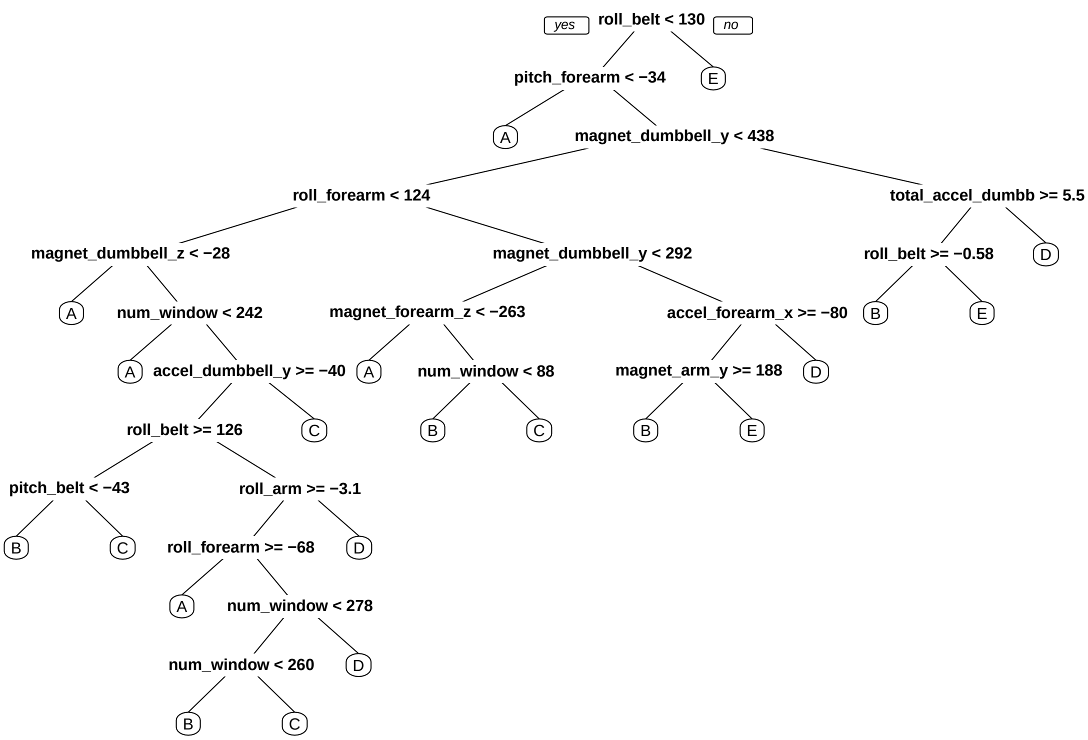
```
## [1] 20 54
```

Data Modeling

Decision Tree

Predictive model for activity recognition

```r
modelTree <- rpart(classe ~ ., data = training, method = "class")
prp(modelTree)
```



Performance of the model on the validation data set

```r
predictTree <- predict(modelTree, validation, type = "class")
confusionMatrix(validation$classe, predictTree)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1526   41   20   61   26
##          B  264  646   74  126   29
##          C   20   56  852   72   26
##          D   93   31  133  665   42
##          E   82   85   93  128  694
##
## Overall Statistics
##
##                Accuracy : 0.7448
##                  95% CI : (0.7334, 0.7559)
##     No Information Rate : 0.3373
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.6754
##  Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.7688   0.7520   0.7270   0.6321   0.8494
## Specificity            0.9621   0.9019   0.9631   0.9381   0.9234
## Pos Pred Value         0.9116   0.5672   0.8304   0.6898   0.6414
## Neg Pred Value         0.8910   0.9551   0.9341   0.9214   0.9744
## Prevalence             0.3373   0.1460   0.1992   0.1788   0.1388
## Detection Rate         0.2593   0.1098   0.1448   0.1130   0.1179
## Detection Prevalence   0.2845   0.1935   0.1743   0.1638   0.1839
## Balanced Accuracy      0.8654   0.8270   0.8450   0.7851   0.8864
```

```
accuracy <- postResample(predictTree, validation$classe)
ose <- 1 - as.numeric(confusionMatrix(validation$classe, predictTree)$overall[1])
rm(predictTree)
rm(modelTree)
```

Random Forest

Being the training size 70 % of total dataset, the bias can not be ignored and k=5 is reasonable [Choice of K in K-fold cross-validation]https://stats.stackexchange.com/questions/27730/choice-of-k-in-k-fold-cross-validation)

```
modelRF <- train(classe ~ ., data = training, method = "rf", trControl = trainControl(method = "cv", 5)
modelRF
```

```
## Random Forest
##
## 13737 samples
##    53 predictor
##     5 classes: 'A', 'B', 'C', 'D', 'E'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 10989, 10988, 10991, 10990, 10990
```

```
## Resampling results across tuning parameters:
## 
##   mtry  Accuracy   Kappa    
##    2    0.9941763  0.9926330
##   27    0.9966511  0.9957639
##   53    0.9948310  0.9934612
## 
## Accuracy was used to select the optimal model using  the largest value.
## The final value used for the model was mtry = 27.
```

Now, we estimate the performance of the model on the validation data set.

```
predictRF <- predict(modelRF, validation)
confusionMatrix(validation$classe, predictRF)
```

```
## Confusion Matrix and Statistics
## 
##           Reference
## Prediction    A    B    C    D    E
##          A 1674    0    0    0    0
##          B    3 1136    0    0    0
##          C    0    1 1022    3    0
##          D    0    0    3  961    0
##          E    0    0    0    1 1081
## 
## Overall Statistics
##                                           
##                Accuracy : 0.9981          
##                  95% CI : (0.9967, 0.9991)
##     No Information Rate : 0.285           
##     P-Value [Acc > NIR] : < 2.2e-16       
##                                           
##                   Kappa : 0.9976          
##  Mcnemar's Test P-Value : NA              
## 
## Statistics by Class:
## 
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9982   0.9991   0.9971   0.9959   1.0000
## Specificity            1.0000   0.9994   0.9992   0.9994   0.9998
## Pos Pred Value         1.0000   0.9974   0.9961   0.9969   0.9991
## Neg Pred Value         0.9993   0.9998   0.9994   0.9992   1.0000
## Prevalence             0.2850   0.1932   0.1742   0.1640   0.1837
## Detection Rate         0.2845   0.1930   0.1737   0.1633   0.1837
## Detection Prevalence   0.2845   0.1935   0.1743   0.1638   0.1839
## Balanced Accuracy      0.9991   0.9992   0.9981   0.9976   0.9999
```

```
accuracy <- postResample(predictRF, validation$classe)
ose <- 1 - as.numeric(confusionMatrix(validation$classe, predictRF)$overall[1])
rm(predictRF)
```

Evaluate the model (out-of-Sample Error)

Now, we apply the Random Forest model to the original testing data set downloaded from the data source. We remove the problem_id column first.

```r
rm(accuracy)
rm(ose)
predict(modelRF, testing[, -length(names(testing))])
```

```
##  [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
```

Write the results to a text file for submission

```r
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)
    }
}
```