Predicting quality of exercise movements using data from accelerometers

Andy Vallebueno

February 12, 2019

Executive summary

This report has the objective of fitting a model that predicts the quality of an activity performed at a specific point in time. It uses the Weight Lifting Exercises Dataset, which investigates how well an activity was performed by the wearer of accelerometers. For this dataset, six 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)." While Class A identifies the correct, specified execution of the exercise, the other four classes capture common mistakes made. (Velloso, 2013)

More information on this dataset can be found at the following webpage: http://groupware.les.inf.puc-rio.br/har#dataset#ixzz5fKXfT5aO

Exploratory Analysis

We begin by reading the training and testing data into R and observe that the training dataset consists of 19,622 observations of 160 variables. These belong to six subjects, as per the user_name variable, producing five different movements (A, B, C, D or E), as per the classe variable. This type of movement is the variable that we shall seek to predict with our model. Below is a summary of a portion of the variables included.

```
training<- read.csv("pml-training.csv")
testing<- read.csv("pml-testing.csv")
summary(training[, c(1:20, 160)])
```

```
##        X            user_name    raw_timestamp_part_1 raw_timestamp_part_2
##  Min.   :    1   adelmo  :3892   Min.   :1.322e+09    Min.   :   294
##  1st Qu.: 4906   carlitos:3112   1st Qu.:1.323e+09    1st Qu.:252912
##  Median : 9812   charles :3536   Median :1.323e+09    Median :496380
##  Mean   : 9812   eurico  :3070   Mean   :1.323e+09    Mean   :500656
##  3rd Qu.:14717   jeremy  :3402   3rd Qu.:1.323e+09    3rd Qu.:751891
##  Max.   :19622   pedro   :2610   Max.   :1.323e+09    Max.   :998801
##
##           cvtd_timestamp  new_window    num_window      roll_belt
##  28/11/2011 14:14: 1498   no :19216   Min.   :  1.0   Min.   :-28.90
##  05/12/2011 11:24: 1497   yes:  406   1st Qu.:222.0   1st Qu.:  1.10
##  30/11/2011 17:11: 1440               Median :424.0   Median :113.00
##  05/12/2011 11:25: 1425               Mean   :430.6   Mean   : 64.41
##  02/12/2011 14:57: 1380               3rd Qu.:644.0   3rd Qu.:123.00
##  02/12/2011 13:34: 1375               Max.   :864.0   Max.   :162.00
##  (Other)         :11007
##    pitch_belt          yaw_belt       total_accel_belt kurtosis_roll_belt
##  Min.   :-55.8000   Min.   :-180.00   Min.   : 0.00             :19216
##  1st Qu.:  1.7600   1st Qu.: -88.30   1st Qu.: 3.00    #DIV/0!  :   10
##  Median :  5.2800   Median : -13.00   Median :17.00    -1.908453:    2
##  Mean   :  0.3053   Mean   : -11.21   Mean   :11.31    -0.016850:    1
```

```
##  3rd Qu.: 14.9000   3rd Qu.:  12.90   3rd Qu.:18.00    -0.021024:    1
##  Max.   : 60.3000   Max.   : 179.00   Max.   :29.00    -0.025513:    1
##                                                        (Other)  :  391
##  kurtosis_picth_belt kurtosis_yaw_belt skewness_roll_belt
##           :19216            :19216             :19216
##  #DIV/0!  :   32     #DIV/0!:  406     #DIV/0!  :    9
##  47.000000:    4                       0.000000 :    4
##  -0.150950:    3                       0.422463 :    2
##  -0.684748:    3                       -0.003095:    1
##  -1.750749:    3                       -0.010002:    1
##  (Other)  :  361                       (Other)  :  389
##  skewness_roll_belt.1 skewness_yaw_belt max_roll_belt     max_picth_belt
##           :19216             :19216     Min.   :-94.300   Min.   : 3.00
##  #DIV/0!  :   32      #DIV/0!:  406     1st Qu.:-88.000   1st Qu.: 5.00
##  0.000000 :    4                       Median : -5.100   Median :18.00
##  -2.156553:    3                       Mean   : -6.667   Mean   :12.92
##  -3.072669:    3                       3rd Qu.: 18.500   3rd Qu.:19.00
##  -6.324555:    3                       Max.   :180.000   Max.   :30.00
##  (Other)  :  361                       NA's   :19216     NA's   :19216
##   max_yaw_belt   classe
##          :19216   A:5580
##  -1.1    :   30   B:3797
##  -1.4    :   29   C:3422
##  -1.2    :   26   D:3216
##  -0.9    :   24   E:3607
##  -1.3    :   22
##  (Other):  275
```

Given the large size of the training set, we will create a validation set and then proceed to the exploratory analysis on our resulting training set.

```
set.seed(411)
inTrain<- createDataPartition(y = training$classe, p = 0.8, list = FALSE)
trainingset<- training[inTrain,]; validationset<- training[-inTrain,]
```

We notice that there are several NA values and proceed to count them in order to identify which variables are useful for prediction. We observe that 67 variables have a missing value rate of 97.9%, indicating that these may not be so useful for prediction. Moreover, we observe that in the cases where these variables have a value of "NA", 34 other variables have a blank value. From here on, we will only focus on the remaining variables as there is not information on the previously mentioned variables to use these for prediction.

```
NAvalues<-NULL
for (i in 1:160) {
  if (mean(is.na(trainingset[,i])) != 0) {
    NAvalues[i]<-i
  } else {NAvalues[i]<-0}

}

Blankvalues<-NULL
for (i in 1:160) {
  if (class(trainingset[1, i]) == "factor" & trainingset[1, i] == "") {
    Blankvalues[i]<-i
  } else {
    Blankvalues[i]<-0
    }
```

```
}
combined<-c(NAvalues, Blankvalues)
combined<-combined[combined != 0]
newtrainingset<- trainingset[, -combined]
```

We check that we have maintained variables with enough variability with the following zero covariate analysis.

```
nsv<-nearZeroVar(newtrainingset, saveMetrics = TRUE)
nsv
```

```
##                       freqRatio percentUnique zeroVar   nzv
## X                      1.000000  100.00000000   FALSE FALSE
## user_name              1.117773    0.03821899   FALSE FALSE
## raw_timestamp_part_1   1.032258    5.33154978   FALSE FALSE
## raw_timestamp_part_2   1.250000   88.17122110   FALSE FALSE
## cvtd_timestamp         1.002498    0.12739665   FALSE FALSE
## new_window            47.453704    0.01273966   FALSE  TRUE
## num_window             1.032258    5.45257660   FALSE FALSE
## roll_belt              1.086957    7.50366265   FALSE FALSE
## pitch_belt             1.006452   11.06439901   FALSE FALSE
## yaw_belt               1.124365   11.79692974   FALSE FALSE
## total_accel_belt       1.079528    0.18472514   FALSE FALSE
## gyros_belt_x           1.061510    0.80896872   FALSE FALSE
## gyros_belt_y           1.166108    0.43314861   FALSE FALSE
## gyros_belt_z           1.059901    1.07013186   FALSE FALSE
## accel_belt_x           1.078947    1.03828269   FALSE FALSE
## accel_belt_y           1.146040    0.89814638   FALSE FALSE
## accel_belt_z           1.085631    1.89184024   FALSE FALSE
## magnet_belt_x          1.112281    1.94916874   FALSE FALSE
## magnet_belt_y          1.092157    1.88547041   FALSE FALSE
## magnet_belt_z          1.002646    2.84094528   FALSE FALSE
## roll_arm              52.423077   15.81629403   FALSE FALSE
## pitch_arm             90.900000   18.52984267   FALSE FALSE
## yaw_arm               34.948718   17.28135550   FALSE FALSE
## total_accel_arm        1.016598    0.42040894   FALSE FALSE
## gyros_arm_x            1.053922    4.05758329   FALSE FALSE
## gyros_arm_y            1.504902    2.35683802   FALSE FALSE
## gyros_arm_z            1.140811    1.51602013   FALSE FALSE
## accel_arm_x            1.114504    4.91751067   FALSE FALSE
## accel_arm_y            1.142857    3.37601121   FALSE FALSE
## accel_arm_z            1.138614    4.90477100   FALSE FALSE
## magnet_arm_x           1.044776    8.48461685   FALSE FALSE
## magnet_arm_y           1.071429    5.49716542   FALSE FALSE
## magnet_arm_z           1.094118    8.01961908   FALSE FALSE
## roll_dumbbell          1.026316   85.57869928   FALSE FALSE
## pitch_dumbbell         2.153846   83.41932607   FALSE FALSE
## yaw_dumbbell           1.271739   85.08185235   FALSE FALSE
## total_accel_dumbbell   1.079890    0.27390280   FALSE FALSE
## gyros_dumbbell_x       1.010040    1.49054080   FALSE FALSE
## gyros_dumbbell_y       1.266667    1.73259443   FALSE FALSE
## gyros_dumbbell_z       1.042945    1.26122683   FALSE FALSE
## accel_dumbbell_x       1.014440    2.66258997   FALSE FALSE
## accel_dumbbell_y       1.019802    2.93012294   FALSE FALSE
## accel_dumbbell_z       1.169399    2.57341232   FALSE FALSE
## magnet_dumbbell_x      1.013889    6.96222689   FALSE FALSE
```

```
## magnet_dumbbell_y     1.186207    5.33791961   FALSE FALSE
## magnet_dumbbell_z     1.013514    4.25504809   FALSE FALSE
## roll_forearm         10.881944   12.72692528   FALSE FALSE
## pitch_forearm        65.270833   17.42786165   FALSE FALSE
## yaw_forearm          15.660000   11.82240907   FALSE FALSE
## total_accel_forearm   1.135406    0.43951844   FALSE FALSE
## gyros_forearm_x       1.062350    1.85362125   FALSE FALSE
## gyros_forearm_y       1.033003    4.61812854   FALSE FALSE
## gyros_forearm_z       1.181579    1.84725142   FALSE FALSE
## accel_forearm_x       1.082192    4.97483916   FALSE FALSE
## accel_forearm_y       1.023529    6.25517549   FALSE FALSE
## accel_forearm_z       1.098361    3.61169501   FALSE FALSE
## magnet_forearm_x      1.033898    9.44646156   FALSE FALSE
## magnet_forearm_y      1.188406   11.75234091   FALSE FALSE
## magnet_forearm_z      1.020408   10.47837442   FALSE FALSE
## classe                1.469388    0.03184916   FALSE FALSE
```

Given the number of variables, we calculate a correlation matrix on the numeric variables. We observe that several variables have a correlation higher than 0.80.

```
correlations<- abs(cor(newtrainingset[, -c(1, 2 ,3 , 4 ,5 , 6, 60)]))
diag(correlations)<-0
correlations<- as.data.frame(correlations)
subcor<-correlations[correlations > 0.8]
subcor
```

```
##  [1] 0.8163596 0.9808708 0.9237196 0.9919226 0.9657924 0.8875411 0.8163596
##  [8] 0.9808708 0.9270899 0.9745665 0.9657924 0.8919023 0.9237196 0.9270899
## [15] 0.9322608 0.9919226 0.9745665 0.9322608 0.8875411 0.8919023 0.9177242
## [22] 0.9177242 0.8160718 0.8160718 0.8140338 0.8140338 0.8098581 0.8479521
## [29] 0.9831733 0.9308973 0.9831733 0.9456068 0.8098581 0.8479521 0.8636651
## [36] 0.9308973 0.9456068 0.8636651
```

Model selection

Since our objective is to predict a factor variable with 5 levels, we will focus on non-linear models. We will start with a classification tree to get an idea of accuracy metrics. We note that this first model (Model 1) has 15,699 nodes and a relatively low accuracy of 66%. As detailed in the confusion matrix, the model correctly classifies A, B and E classes, but incorrectly classifies as E all those observations from the C and D classes.

```
set.seed(411)
model1<- train(classe ~ . , data = newtrainingset, method = "rpart")
print(model1$finalModel)
```

```
## n= 15699
##
## node), split, n, loss, yval, (yprob)
##       * denotes terminal node
##
## 1) root 15699 11235 A (0.28 0.19 0.17 0.16 0.18)
##   2) X< 5580.5 4464     0 A (1 0 0 0 0) *
##   3) X>=5580.5 11235  8197 B (0 0.27 0.24 0.23 0.26)
##     6) X< 9377.5 3038     0 B (0 1 0 0 0) *
##     7) X>=9377.5 8197  5311 E (0 0 0.33 0.31 0.35) *
```

```
model1predictions<- predict(model1, newdata = validationset)
confusionMatrix(validationset$classe, model1predictions)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1116    0    0    0    0
##          B    0  759    0    0    0
##          C    0    0    0    0  684
##          D    0    0    0    0  643
##          E    0    0    0    0  721
##
## Overall Statistics
##
##                Accuracy : 0.6617
##                  95% CI : (0.6467, 0.6765)
##     No Information Rate : 0.522
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.5695
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   1.0000       NA       NA   0.3521
## Specificity            1.0000   1.0000   0.8256   0.8361   1.0000
## Pos Pred Value         1.0000   1.0000       NA       NA   1.0000
## Neg Pred Value         1.0000   1.0000       NA       NA   0.5856
## Prevalence             0.2845   0.1935   0.0000   0.0000   0.5220
## Detection Rate         0.2845   0.1935   0.0000   0.0000   0.1838
## Detection Prevalence   0.2845   0.1935   0.1744   0.1639   0.1838
## Balanced Accuracy      1.0000   1.0000       NA       NA   0.6760
```

We now fit a second model, a random forest model, to compare. We note that there is an important trade-off here in terms of accuracy and speed compared to our first model. Accuracy for Model 2 increases to 100%, although it is much more computationally demanding and subject to overfitting. We note that in this section we are using cross validation as the resampling method in the trainControl function, and changing to 5 the number that specifies the quantity of folds for k-fold cross validation.

```
cluster<-makeCluster(detectCores() - 1)
registerDoParallel(cluster)
fitControl<- trainControl(method = "cv", number = 5, allowParallel = TRUE)
model2<- train(classe ~ . , data = newtrainingset, method = "rf", trControl = fitControl)
stopCluster(cluster)
registerDoSEQ()

print(model2$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: 41
##
```

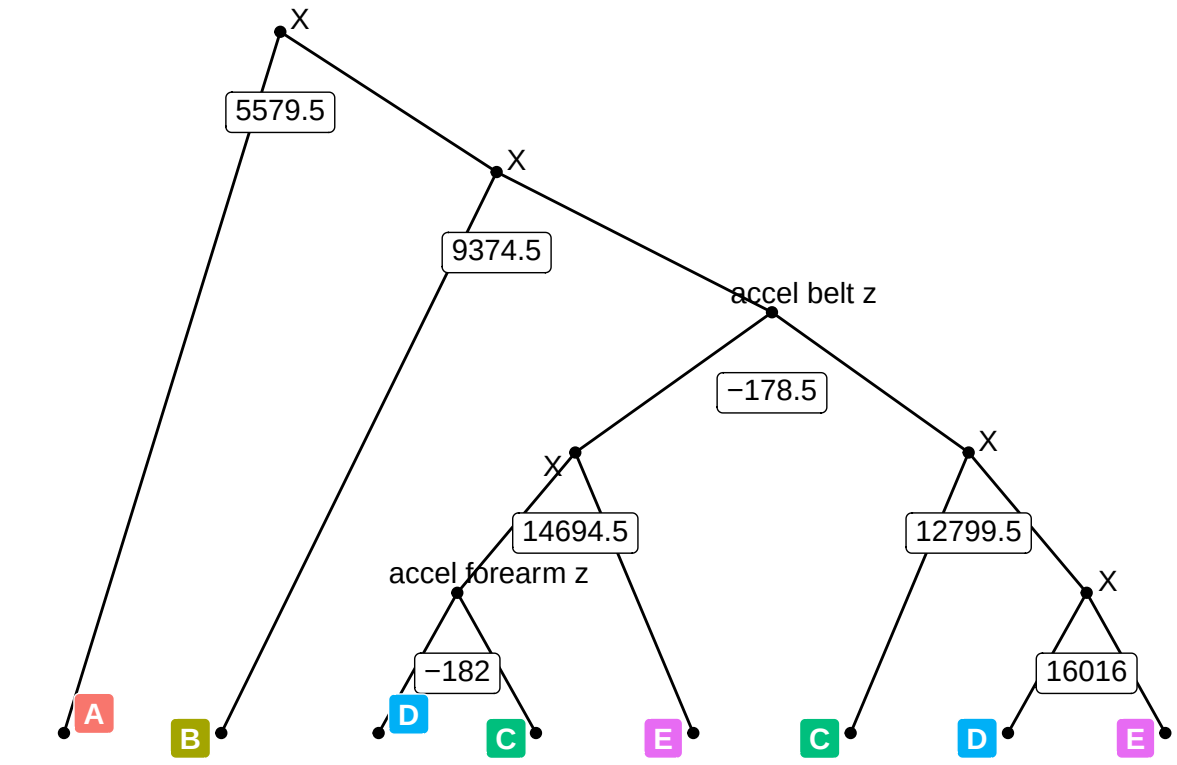
```
##         OOB estimate of  error rate: 0.02%
## Confusion matrix:
##      A    B    C    D    E  class.error
## A 4464    0    0    0    0 0.0000000000
## B    1 3036    1    0    0 0.0006583278
## C    0    1 2737    0    0 0.0003652301
## D    0    0    0 2573    0 0.0000000000
## E    0    0    0    0 2886 0.0000000000
```

```
model2predictions<- predict(model2, newdata = validationset)
confusionMatrix(validationset$classe, model2predictions)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1116    0    0    0    0
##          B    0  759    0    0    0
##          C    0    0  684    0    0
##          D    0    0    0  643    0
##          E    0    0    0    0  721
##
## Overall Statistics
##
##                Accuracy : 1
##                  95% CI : (0.9991, 1)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 1
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   1.0000   1.0000   1.0000   1.0000
## Specificity            1.0000   1.0000   1.0000   1.0000   1.0000
## Pos Pred Value         1.0000   1.0000   1.0000   1.0000   1.0000
## Neg Pred Value         1.0000   1.0000   1.0000   1.0000   1.0000
## Prevalence             0.2845   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2845   0.1935   0.1744   0.1639   0.1838
## Detection Prevalence   0.2845   0.1935   0.1744   0.1639   0.1838
## Balanced Accuracy      1.0000   1.0000   1.0000   1.0000   1.0000
```

For purely visual purposes, we now graph one of the trees from our model to get an idea of how the variables are interacting. We have chosen to plot tree k= 1. Note that the code for this graph, which is purely to illustrate our model, has been sourced from Shirin's playgRound and can be found at this webpage: https://shiring.github.io/machine_learning/2017/03/16/rf_plot_ggraph. Please find full reference in the Sources section.

```
tree_func(final_model = model2$finalModel, 1)
```



Conclusions

Following an exploratory analysis and model selection process, we have fitted a random forest model with strong accuracy metrics on our validation data set which classifies the quality of a particular activity using 60 variables. This model will be used on a testing set to predict the class or quality of movement of 20 different observations. Although our in sample error is relatively low, we know that the out of sample error or generalization error will be slightly higher, particularly due to overfitting in random forest models. However, we expect an adequate performance.

Sources

Glander, Shirin. Plotting trees from Random Forest models with ggraph. Shirin's playgRound. 2019. URL: https://shiring.github.io/machine_learning/2017/03/16/rf_plot_ggraph

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.