

# Human activity recognition

## Summary

The *Weight Lifting Exercises Dataset* described and analyzed in the article *Qualitative Activity Recognition of Weight Lifting Exercises* by Velloso, E. et al. (see Human Activity Recognition (<http://groupware.les.inf.puc-rio.br/har>)) contains data about 5 different barbell lifting exercises performed by 5 young people. These exercises have been classified in five categories (A, B, C, D, E). Category A corresponds to correct execution while B, C, D, E are different errors of execution. The objective of our analysis is to assess the capability of the measured variables to predict the category to which exercises belong.

## Analysis

Our analysis will not be based on the original dataset that can be downloaded at WLE dataset ([http://groupware.les.inf.puc-rio.br/static/WLE/WearableComputing\\_weight\\_lifting\\_exercises\\_biceps\\_curl\\_variations.csv](http://groupware.les.inf.puc-rio.br/static/WLE/WearableComputing_weight_lifting_exercises_biceps_curl_variations.csv)) but on files *pml-training.csv* and *pml-testing* files that can be downloaded at Practical machine learning ([https://class.coursera.org/predmachlearn-002/human\\_grading/view/courses/972090/assessments/4/submissions](https://class.coursera.org/predmachlearn-002/human_grading/view/courses/972090/assessments/4/submissions)).

## Data preparation

We start by reading the data:

```
training<-read.csv("pml-training.csv")
testing<-read.csv("pml-testing.csv")
```

The subsequent step is to transform the output variable classe in a factor

```
training$classe<-as.factor(training$classe)
```

The training data set contains 160 variables and 19622 observations. The test set contains 160 variables and 20 observations.

To reduce the dataset we first remove near zero values:

```
options(warn=-1)
suppressPackageStartupMessages(library(caret))
nzv <- nearZeroVar(training, saveMetrics=TRUE)
omit <- which(nzv$nzv==TRUE)
training <- training[,-omit]
testing <- testing[,-omit]
```

This reduces the number of variables from 160 to 100. Variables can be further reduced by removing those that contain a high percentage of null values

```
notNullColumns<-colSums(is.na(training)) < 19000
training<-training[,notNullColumns]
testing<-testing[,notNullColumns]
```

This reduces the number of variables to 59.

The last step we perform to make computation faster is the random selection of 3000 rows:

```
numberOfRows<-3000
trainInds <- sample(nrow(training), numberOfRows)
training <- training[trainInds,]
```

We point out that the number 3000 is arbitrary and can be modified if desired.

## Data analysis

Since our testing dataset is too small (20 observations) and does not contain the classe variable we split our training dataset into a training subset and a test subset:

```
trainIndex <-createDataPartition(training$classe,p=0.6,list=FALSE)
training.train<-training[trainIndex,]
training.test<-training[-trainIndex,]
```

We are now ready to analyze our data using random forests:

```
suppressMessages(library(randomForest))
modFit<-train(classe~.,data=training.train,method="rf",prox=TRUE,preProcess=c("center", "scale"))
modFit$results
```

```
##      mtry Accuracy   Kappa AccuracySD   KappaSD
## 1      2   0.9551 0.9432    0.008801 0.011108
## 2     41   0.9983 0.9978    0.001455 0.001847
## 3     80   0.9980 0.9974    0.001463 0.001857
```

We can now test our model on our test set:

```
prediction<-predict(modFit,training.test)
table(prediction,training.test$classe)
```

```
##
## prediction    A    B    C    D    E
##           A 342    0    0    0    0
##           B   0 217    0    0    0
##           C   0   0 217    0    0
##           D   0   0   0 201    0
##           E   0   0   0   0 220
```

```
confusionMatrix<-confusionMatrix(prediction,training.test$classe)
confusionMatrix$byClass[,c(1,2,8)]
```

```
##           Sensitivity Specificity Balanced Accuracy
## Class: A           1           1           1
## Class: B           1           1           1
## Class: C           1           1           1
## Class: D           1           1           1
## Class: E           1           1           1
```

The accuracy provides us with the desired out-of-sample error estimate. Last but not least we apply our prediction to the original test set

```
prediction<-predict(modFit,testing)
prediction
```

```
##  [1] A A A A A A A A A A A A A A A A A A
## Levels: A B C D E
```