

# Practical Machine Learning Wk 4

ekonomix

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## Executive Summary

We have data from 4 sensors placed on participants bodies and object (belt, forearm, arm and the dumbbell); they measure how the different body parts and the dumbbell itself are moving as the participant is attempting to lift it.

Participants were asked to lift the dumbbell in 5 different ways, 1 correct way and 4 'wrong' ways. Our aim is to distinguish "how well" the exercise is taking place, hence using the sensor data distinguish between these different types of lift.

## load some libraries we are likely to be using

```
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

library(ggplot2)
```

## Get data - download as csv and load

```
Urla <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-
training.csv"
Urlb <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"
training <- read.csv(url(Urla), na.strings=c("NA", "#DIV/0!", ""))
testing <- read.csv(url(Urlb), na.strings=c("NA", "#DIV/0!", ""))
```

## take a look at the data

```
dim(training)

## [1] 19622 160

#str(training) # not shown in output
dim(testing)

## [1] 20 160

#str(testing) # not shown in output
```

it looks like the first 7 variables have no predictive value for this exercise

## get rid of variables with many NAs and variables expected to have no predictive value in this case

```
NA_Count = sapply(1:dim(training)[2],function(x)sum(is.na(training[,x])))
NA_Count

## [1] 0 0 0 0 0 0 0 0 0 0 0 0
## [12] 19226 19248 19622 19225 19248 19622 19216 19216 19226 19216 19216
## [23] 19226 19216 19216 19226 19216 19216 19216 19216 19216 19216 19216
## [34] 19216 19216 19216 0 0 0 0 0 0 0 0
## [45] 0 0 0 0 0 19216 19216 19216 19216 19216 19216
## [56] 19216 19216 19216 19216 0 0 0 0 0 0 0
## [67] 0 0 19294 19296 19227 19293 19296 19227 19216 19216 19216
## [78] 19216 19216 19216 19216 19216 19216 0 0 0 19221 19218
## [89] 19622 19220 19217 19622 19216 19216 19221 19216 19216 19221 19216
## [100] 19216 19221 0 19216 19216 19216 19216 19216 19216 19216 19216
## [111] 19216 19216 0 0 0 0 0 0 0 0 0
## [122] 0 0 0 19300 19301 19622 19299 19301 19622 19216 19216
## [133] 19300 19216 19216 19300 19216 19216 19300 0 19216 19216 19216
## [144] 19216 19216 19216 19216 19216 19216 19216 0 0 0 0
## [155] 0 0 0 0 0 0 0

NA_list = which(NA_Count>0)
```

## modify the training and test data sets to remove unnecessary columns and transforming the class into a factor

```
training_clean <- training[,-NA_list]
training_clean <- training_clean[,-c(1:7)]
training_clean$classe = factor(training_clean$classe)

testing_clean <- testing[,-NA_list]
testing_clean <- testing_clean[,-c(1:7)]
```

*# head(testing\_clean) # not shown in output*

## build models and deciding which works best

## this is a classification problem, and we'll try random forest and classification tree

```
set.seed(2501)
```

Random Forest

```
rffit <- train(classe ~ ., method = "rf", data = training_clean, importance =
T, trControl = trainControl(method = "cv", number = 3))
```

```
## Loading required package: 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

#training performance
training_rfpred <- predict(rfFit, newdata=training_clean)
rf_confusion <- confusionMatrix(training_rfpred, training_clean$classe)
rf_confusion

## Confusion Matrix and Statistics
##
##              Reference
## Prediction      A      B      C      D      E
##      A 5580      0      0      0      0
##      B      0 3797      0      0      0
##      C      0      0 3422      0      0
##      D      0      0      0 3216      0
##      E      0      0      0      0 3607
##
## Overall Statistics
##
##              Accuracy : 1
##              95% CI : (0.9998, 1)
##      No Information Rate : 0.2844
##      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        0.2844      0.1935      0.1744      0.1639      0.1838
## Detection Rate     0.2844      0.1935      0.1744      0.1639      0.1838
## Detection Prevalence 0.2844      0.1935      0.1744      0.1639      0.1838
## Balanced Accuracy    1.0000      1.0000      1.0000      1.0000      1.0000
```

*#Looks good*

## Random Forest Results look good!

Classification Tree

```
rpartFit <- train(classe ~ ., method = "rpart", data = training_clean)
```

```
## Loading required package: rpart
```

*#training performance*

```
training_rpartpred <- predict(rpartFit, newdata=training_clean)
confusionMatrix(training_rpartpred, training_clean$classe)
```

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

```
##
```

```
##           Reference
```

```
## Prediction   A    B    C    D    E
##           A 5080 1581 1587 1449  524
##           B   81 1286  108  568  486
##           C  405  930 1727 1199  966
##           D    0    0    0    0    0
##           E   14    0    0    0 1631
```

```
##
```

```
## Overall Statistics
```

```
##
```

```
##           Accuracy : 0.4956
```

```
##           95% CI : (0.4885, 0.5026)
```

```
## No Information Rate : 0.2844
```

```
## P-Value [Acc > NIR] : < 2.2e-16
```

```
##
```

```
##           Kappa : 0.3407
```

```
## McNemar's Test P-Value : NA
```

```
##
```

```
## Statistics by Class:
```

```
##
```

```
##           Class: A Class: B Class: C Class: D Class: E
## Sensitivity      0.9104 0.33869 0.50468 0.0000 0.45218
## Specificity      0.6339 0.92145 0.78395 1.0000 0.99913
## Pos Pred Value   0.4970 0.50850 0.33040      NaN 0.99149
## Neg Pred Value    0.9468 0.85310 0.88225 0.8361 0.89008
## Prevalence       0.2844 0.19351 0.17440 0.1639 0.18382
## Detection Rate    0.2589 0.06554 0.08801 0.0000 0.08312
## Detection Prevalence 0.5209 0.12889 0.26638 0.0000 0.08383
## Balanced Accuracy 0.7721 0.63007 0.64431 0.5000 0.72565
```

*#not as good*

Regressions trees are nto as good as random forest here.

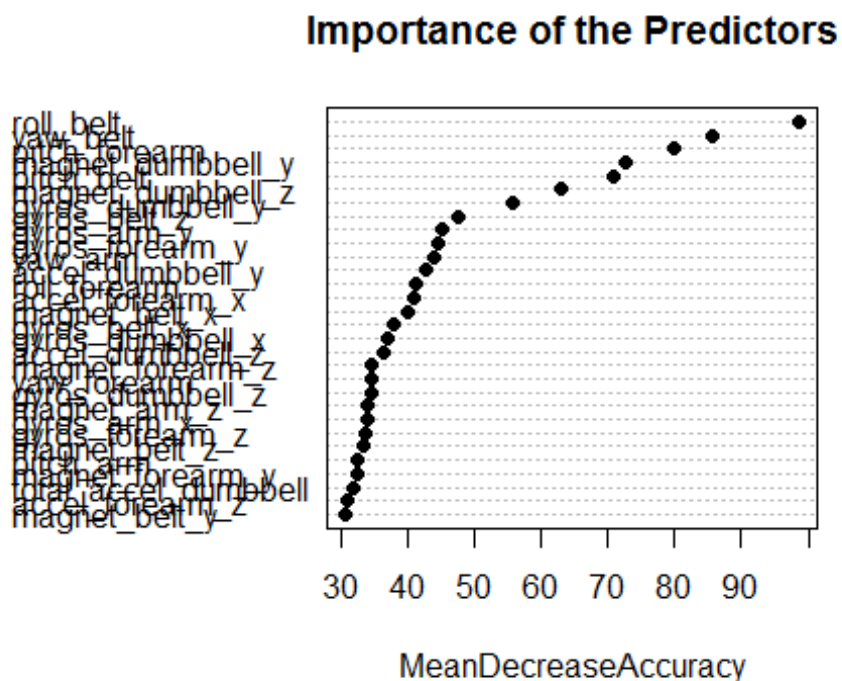
Hence Random Forest is Chosen!

important variables, expected error (1-accuracy) and predictions for test data:

```
#Important Variables
```

```
imp_rf <- varImp(rfFit)$importance
```

```
varImpPlot(rfFit$finalModel, sort = TRUE, type = 1, pch = 19, col = 1, cex = 1, main = "Importance of the Predictors")
```



```
#accuracy and expected error
```

```
attributes(rf_confusion)
```

```
## $names
```

```
## [1] "positive" "table" "overall" "byClass" "mode" "dots"
```

```
##
```

```
## $class
```

```
## [1] "confusionMatrix"
```

```
rf_confusion$overall
```

```
## Accuracy Kappa AccuracyLower AccuracyUpper AccuracyNull
## 1.0000000 1.0000000 0.9998120 1.0000000 0.2843747
## AccuracyPValue McNemarPValue
## 0.0000000 NaN
```

```

rf_confusion$overall['Accuracy']

## Accuracy
##      1

rf_confusion$overall['AccuracyUpper']

## AccuracyUpper
##      1

rf_confusion$overall['AccuracyLower']

## AccuracyLower
##    0.999812

testing_rfpred <- predict(rfFit, newdata=testing_clean)
testing_rfpred

## [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

```

## writing out the predictions

```

pml_write_files = function(x){
  n = length(x)
  for(i in 1:n){
    filename = paste0("./practical_ml_wk4_",i,".txt")

write.table(x[i],file=filename,quote=FALSE,row.names=FALSE,col.names=FALSE)
  }
}

pml_write_files(testing_rfpred)

testing_rfpred

## [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

```