Final Project for Data Science Course 8 Week 4

NguyenDuy
19 February 2017

Reading data

There are two types of variable in data: raw variable (about 19500 data point and 20 data point for each variable in training and testing data set, respectively) and summary variable (402 data point and 0 data point for each variable in training and testing data set, respectively). There are 60 raw variable and 100 summary variable in both set. Because in testing data set, only raw variables are provided, thus we only pick out raw variable to construct training model.

```
data <- read.csv("pml-training.csv")</pre>
                                                 #Read training data
data[data == ""] <- NA
                                                 #Clean-up testing data
testingData <- read.csv("pml-testing.csv")</pre>
                                                 #Read testing data
testingData[testingData == ""] <- NA
                                                 #Clean-up testing data
#Cross table of variable and number of variable in training data,
#showing 60 raw variables and 100 summary variables
table(apply(data, 2, function(x){sum(!is.na(x))}))
##
##
     406 19622
##
     100
            60
#Cross table of variable and number of variable in testing data,
#showing 60 raw variables and 100 summary variables
table(apply(testingData, 2, function(x){sum(!is.na(x))}))
##
##
     0
        20
## 100
       60
#Sample of names of raw variables
apply(data, 2, function(x){sum(!is.na(x))}) %>% .[. == 19622] %>% names %>% head
## [1] "X"
                               "user_name"
                                                      "raw_timestamp_part_1"
## [4] "raw_timestamp_part_2" "cvtd_timestamp"
                                                      "new_window"
#Sample of names of summary variables
apply(data, 2, function(x){sum(!is.na(x))}) %>% .[. == 406] %>% names %>% head
                               "kurtosis_picth_belt" "kurtosis_yaw_belt"
## [1] "kurtosis_roll_belt"
                               "skewness_roll_belt.1" "skewness_yaw_belt"
## [4] "skewness_roll_belt"
```

Extract data into two set: raw variable (set2) and summary variable (set1). We only use set 2 variable in this project.

```
set1 <- names(data)[apply(data, 2, function(x){sum(!is.na(x))})==406]
set2 <- names(data)[apply(data, 2, function(x){sum(!is.na(x))})>406]
```

Cleaning data

From raw data set (set2), we exclude column 1-7, which is only identifier and not real data variable.

```
data[,set2][,c(-1:-7)] -> extract2
```

Model construction

We use random forest machine learning method to construct identifier model.

```
library(randomForest)
model2 <- randomForest(classe~., extract2)</pre>
model2
##
## Call:
  randomForest(formula = classe ~ ., data = extract2)
##
                  Type of random forest: classification
##
                        Number of trees: 500
## No. of variables tried at each split: 7
##
           OOB estimate of error rate: 0.3%
## Confusion matrix:
            B C
##
                       D
                            E class.error
       Α
## A 5578
                  0
                       0
                            1 0.0003584229
            1
## B
       9 3785
                  3
                       0
                            0 0.0031603898
       0
           11 3409
                       2
                            0 0.0037989480
                            2 0.0077736318
## D
       0
            0
                23 3191
## E
                       6 3601 0.0016634322
```

Predicting test set

```
testingDataExtract <- testingData[, names(extract2)[-length(names(extract2))]]
result <- predict(model2, testingDataExtract)
tomatch <- c("A", "B", "C", "D", "E")
finalResult <- sapply(result, function(x){tomatch[x]})
finalResult

## [1] "B" "A" "B" "A" "A" "E" "D" "B" "A" "A" "B" "C" "B" "A" "E" "E" "A"
## [18] "B" "B" "B"</pre>
```

Degree of accuracy

```
k <- 0
for(i in 1:5){k <- k + model2$confusion[i,i]}
k/sum(model2$confusion[,1:5])</pre>
```

[1] 0.9970441

Finding important variable

List of variable sorted by the degree of imporant are shown below, which the most imporant as row 1

```
varImportance <- importance(model2, type = 2)
varImportance[order(-varImportance),]</pre>
```

##	roll_belt	yaw_belt	pitch_forearm
##	1260.94087	906.72709	801.18286
##	magnet_dumbbell_z	magnet_dumbbell_y	pitch_belt
##	761.29824	695.57549	694.44510
##	${\tt roll_forearm}$	${\tt magnet_dumbbell_x}$	accel_dumbbell_y
##	622.08928	477.79441	413.17108
##	roll_dumbbell	accel_belt_z	magnet_belt_z
##	409.34824	403.11817	396.22404
##	magnet_belt_y	$accel_dumbbell_z$	$accel_forearm_x$
##	370.08028	336.93902	319.70536
##	$roll_arm$	${ t gyros_belt_z}$	magnet_forearm_z
##	313.69908	312.08810	286.81908
##	total_accel_dumbbell	$yaw_dumbbell$	<pre>gyros_dumbbell_y</pre>
##	265.81978	265.27781	256.59256
##	${\tt magnet_belt_x}$	$accel_arm_x$	${\tt magnet_arm_x}$
##	254.33541	249.39330	244.99918
##	accel_dumbbell_x	accel_forearm_z	yaw_arm
##	244.38144	234.42127	228.88651
##	${\tt magnet_arm_y}$	magnet_forearm_y	total_accel_belt
##	224.59700	221.11397	212.85282
##	${\tt magnet_forearm_x}$	${\tt magnet_arm_z}$	pitch_arm
##	206.75317	187.28522	176.08424
##	<pre>yaw_forearm</pre>	pitch_dumbbell	accel_arm_y
##	175.79900	175.28250	160.39207
##	accel_forearm_y	gyros_arm_y	gyros_arm_x
##	143.12395	136.74591	133.67342
##	accel_belt_y	accel_arm_z	<pre>gyros_dumbbell_x</pre>
##	133.12769	129.25058	127.04456
##	<pre>gyros_forearm_y</pre>	gyros_belt_y	accel_belt_x
##	119.94187	112.79408	111.00654
##	total_accel_forearm	total_accel_arm	gyros_belt_x
##	108.05437	100.15243	94.66080
##	gyros_forearm_z	gyros_dumbbell_z	gyros_forearm_x
##	83.68985	81.38829	73.77335
##	gyros_arm_z		
##	58.18472		