Title: "Quantified Self Movement Prediction Assignment"

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Background

Using devices such as JawboneUp, NikeFuelBand, and Fitbitit is now possible to collect a large amount of data about personal activity relatively inexpensively. These type of devices are part of the quantified self movement - a group of enthusiasts who take measurements about themselves regularly to improve their health, to find patterns in their behavior, or because they are tech geeks. One thing that people regularly do is quantify how much of a particular activity they do, but they rarely quantify how well they do it.

In this assignment, the goal is to use data from accelerometers on the belt, forearm, arm, and dumbell of 6 participants and develop a machine learning algorithm. 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).

Data and R packages

Load packages, set caching

```
## Loading required package: caret

## Warning: package 'caret' was built under R version 3.2.5

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

## Warning: package 'ggplot2' was built under R version 3.2.5

## Loading required package: corrplot

## Warning: package 'corrplot' was built under R version 3.2.5

## Loading required package: Rtsne

## Warning in library(package, lib.loc = lib.loc, character.only = TRUE,
## logical.return = TRUE, : there is no package called 'Rtsne'

## Loading required package: knitr
```

Getting Data

Set the variables for the URL of training and testing data

```r
train.link <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
test.link <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"
```

Set the variables for the file names

```r
train.fname <- "pml-training.csv"
test.fname <- "pml-testing.csv"

# if files does not exist, download the files

if (!file.exists(train.fname)) {
  download.file(train.link, destfile=train.fname, method="curl")
}
if (!file.exists(test.fname)) {
  download.file(test.link, destfile=test.fname, method="curl")
}
# load the CSV files as data.frame
train.data = read.csv("pml-training.csv")
test.data = read.csv("pml-testing.csv")
names(train.data)
```

```
##   [1] "X"                          "user_name"
##   [3] "raw_timestamp_part_1"       "raw_timestamp_part_2"
##   [5] "cvtd_timestamp"             "new_window"
##   [7] "num_window"                 "roll_belt"
##   [9] "pitch_belt"                 "yaw_belt"
##  [11] "total_accel_belt"           "kurtosis_roll_belt"
##  [13] "kurtosis_picth_belt"        "kurtosis_yaw_belt"
##  [15] "skewness_roll_belt"         "skewness_roll_belt.1"
##  [17] "skewness_yaw_belt"          "max_roll_belt"
##  [19] "max_picth_belt"             "max_yaw_belt"
##  [21] "min_roll_belt"              "min_pitch_belt"
##  [23] "min_yaw_belt"               "amplitude_roll_belt"
##  [25] "amplitude_pitch_belt"       "amplitude_yaw_belt"
##  [27] "var_total_accel_belt"       "avg_roll_belt"
##  [29] "stddev_roll_belt"           "var_roll_belt"
##  [31] "avg_pitch_belt"             "stddev_pitch_belt"
##  [33] "var_pitch_belt"             "avg_yaw_belt"
##  [35] "stddev_yaw_belt"            "var_yaw_belt"
##  [37] "gyros_belt_x"               "gyros_belt_y"
##  [39] "gyros_belt_z"               "accel_belt_x"
##  [41] "accel_belt_y"               "accel_belt_z"
##  [43] "magnet_belt_x"              "magnet_belt_y"
##  [45] "magnet_belt_z"              "roll_arm"
##  [47] "pitch_arm"                  "yaw_arm"
##  [49] "total_accel_arm"            "var_accel_arm"
##  [51] "avg_roll_arm"               "stddev_roll_arm"
##  [53] "var_roll_arm"               "avg_pitch_arm"
```

```
##  [55] "stddev_pitch_arm"         "var_pitch_arm"
##  [57] "avg_yaw_arm"              "stddev_yaw_arm"
##  [59] "var_yaw_arm"              "gyros_arm_x"
##  [61] "gyros_arm_y"              "gyros_arm_z"
##  [63] "accel_arm_x"              "accel_arm_y"
##  [65] "accel_arm_z"              "magnet_arm_x"
##  [67] "magnet_arm_y"             "magnet_arm_z"
##  [69] "kurtosis_roll_arm"        "kurtosis_picth_arm"
##  [71] "kurtosis_yaw_arm"         "skewness_roll_arm"
##  [73] "skewness_pitch_arm"       "skewness_yaw_arm"
##  [75] "max_roll_arm"             "max_picth_arm"
##  [77] "max_yaw_arm"              "min_roll_arm"
##  [79] "min_pitch_arm"            "min_yaw_arm"
##  [81] "amplitude_roll_arm"       "amplitude_pitch_arm"
##  [83] "amplitude_yaw_arm"        "roll_dumbbell"
##  [85] "pitch_dumbbell"           "yaw_dumbbell"
##  [87] "kurtosis_roll_dumbbell"   "kurtosis_picth_dumbbell"
##  [89] "kurtosis_yaw_dumbbell"    "skewness_roll_dumbbell"
##  [91] "skewness_pitch_dumbbell"  "skewness_yaw_dumbbell"
##  [93] "max_roll_dumbbell"        "max_picth_dumbbell"
##  [95] "max_yaw_dumbbell"         "min_roll_dumbbell"
##  [97] "min_pitch_dumbbell"       "min_yaw_dumbbell"
##  [99] "amplitude_roll_dumbbell"  "amplitude_pitch_dumbbell"
## [101] "amplitude_yaw_dumbbell"   "total_accel_dumbbell"
## [103] "var_accel_dumbbell"       "avg_roll_dumbbell"
## [105] "stddev_roll_dumbbell"     "var_roll_dumbbell"
## [107] "avg_pitch_dumbbell"       "stddev_pitch_dumbbell"
## [109] "var_pitch_dumbbell"       "avg_yaw_dumbbell"
## [111] "stddev_yaw_dumbbell"      "var_yaw_dumbbell"
## [113] "gyros_dumbbell_x"         "gyros_dumbbell_y"
## [115] "gyros_dumbbell_z"         "accel_dumbbell_x"
## [117] "accel_dumbbell_y"         "accel_dumbbell_z"
## [119] "magnet_dumbbell_x"        "magnet_dumbbell_y"
## [121] "magnet_dumbbell_z"        "roll_forearm"
## [123] "pitch_forearm"            "yaw_forearm"
## [125] "kurtosis_roll_forearm"    "kurtosis_picth_forearm"
## [127] "kurtosis_yaw_forearm"     "skewness_roll_forearm"
## [129] "skewness_pitch_forearm"   "skewness_yaw_forearm"
## [131] "max_roll_forearm"         "max_picth_forearm"
## [133] "max_yaw_forearm"          "min_roll_forearm"
## [135] "min_pitch_forearm"        "min_yaw_forearm"
## [137] "amplitude_roll_forearm"   "amplitude_pitch_forearm"
## [139] "amplitude_yaw_forearm"    "total_accel_forearm"
## [141] "var_accel_forearm"        "avg_roll_forearm"
## [143] "stddev_roll_forearm"      "var_roll_forearm"
## [145] "avg_pitch_forearm"        "stddev_pitch_forearm"
## [147] "var_pitch_forearm"        "avg_yaw_forearm"
## [149] "stddev_yaw_forearm"       "var_yaw_forearm"
## [151] "gyros_forearm_x"          "gyros_forearm_y"
## [153] "gyros_forearm_z"          "accel_forearm_x"
```

```
## [155] "accel_forearm_y"          "accel_forearm_z"
## [157] "magnet_forearm_x"         "magnet_forearm_y"
## [159] "magnet_forearm_z"         "classe"
```

Data Preparation

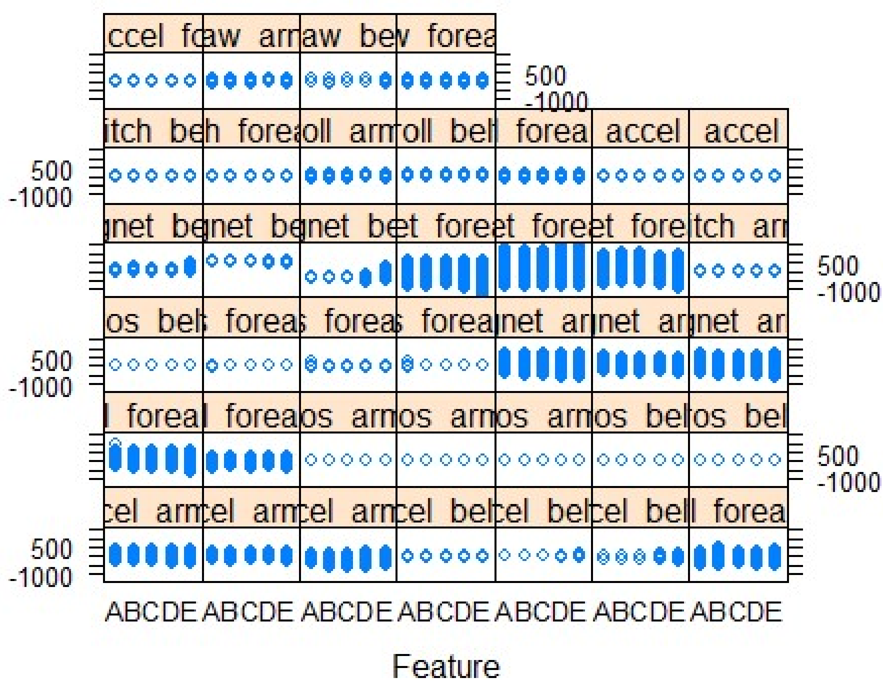
The assignment needs us to use data from accelerometers on the belt, forearm, arm, and dumbell, so the features are extracted based on these keywords along with the classe feature.

```
## [1] "A" "B" "C" "D" "E"

## [1] 1 1 1 1 1 1
## Levels: 1 2 3 4 5
```

Plot the relationship between features and outcome.

```
featurePlot(train, outcome.tmp, "strip")
```



From the above plot, we can see that each feature has relatively the same distribution among the 5 outcome levels (A, B, C, D, E).

Check for features's variance

Based on the principal component analysis(PCA), it is necessary that features have maximum variance for maximum uniqueness, so that each feature is as distant as possible from other features.

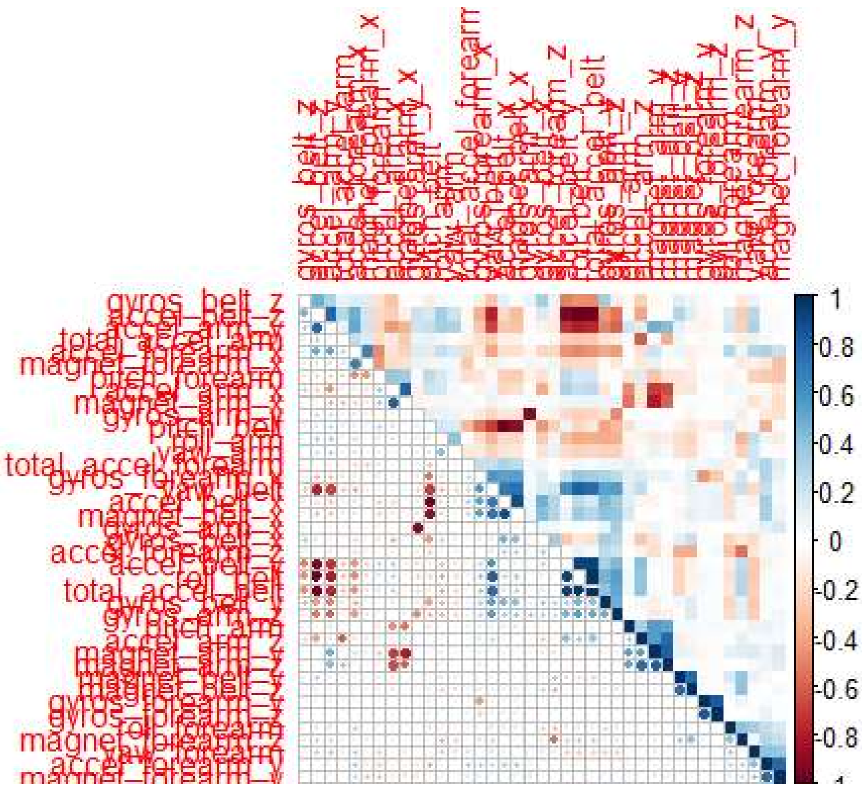
```
# check for zero variance
zvar = nearZeroVar(train, saveMetrics=TRUE)
zvar
```

```
##                      freqRatio percentUnique zeroVar   nzv
## roll_belt             1.101904     6.7781062   FALSE FALSE
## pitch_belt            1.036082     9.3772296   FALSE FALSE
## yaw_belt              1.058480     9.9734991   FALSE FALSE
## total_accel_belt      1.063160     0.1477933   FALSE FALSE
## gyros_belt_x          1.058651     0.7134849   FALSE FALSE
## gyros_belt_y          1.144000     0.3516461   FALSE FALSE
## gyros_belt_z          1.066214     0.8612782   FALSE FALSE
## accel_belt_x          1.055412     0.8357966   FALSE FALSE
## accel_belt_y          1.113725     0.7287738   FALSE FALSE
## accel_belt_z          1.078767     1.5237998   FALSE FALSE
## magnet_belt_x         1.090141     1.6664968   FALSE FALSE
## magnet_belt_y         1.099688     1.5187035   FALSE FALSE
## magnet_belt_z         1.006369     2.3290184   FALSE FALSE
## roll_arm             52.338462    13.5256345   FALSE FALSE
## pitch_arm            87.256410    15.7323412   FALSE FALSE
## yaw_arm              33.029126    14.6570176   FALSE FALSE
## total_accel_arm       1.024526     0.3363572   FALSE FALSE
## gyros_arm_x           1.015504     3.2769341   FALSE FALSE
## gyros_arm_y           1.454369     1.9162165   FALSE FALSE
## gyros_arm_z           1.110687     1.2638875   FALSE FALSE
## accel_arm_x           1.017341     3.9598410   FALSE FALSE
## accel_arm_y           1.140187     2.7367241   FALSE FALSE
## accel_arm_z           1.128000     4.0362858   FALSE FALSE
## magnet_arm_x          1.000000     6.8239731   FALSE FALSE
## magnet_arm_y          1.056818     4.4439914   FALSE FALSE
## magnet_arm_z          1.036364     6.4468454   FALSE FALSE
## roll_forearm         11.589286    11.0895933   FALSE FALSE
## pitch_forearm        65.983051    14.8557741   FALSE FALSE
## yaw_forearm          15.322835    10.1467740   FALSE FALSE
## total_accel_forearm   1.128928     0.3567424   FALSE FALSE
## gyros_forearm_x       1.059273     1.5187035   FALSE FALSE
## gyros_forearm_y       1.036554     3.7763735   FALSE FALSE
## gyros_forearm_z       1.122917     1.5645704   FALSE FALSE
## accel_forearm_x       1.126437     4.0464784   FALSE FALSE
## accel_forearm_y       1.059406     5.1116094   FALSE FALSE
## accel_forearm_z       1.006250     2.9558659   FALSE FALSE
## magnet_forearm_x      1.012346     7.7667924   FALSE FALSE
## magnet_forearm_y      1.246914     9.5403119   FALSE FALSE
## magnet_forearm_z      1.000000     8.5771073   FALSE FALSE
```

It appears that there are no features without variability (all has enough variance). So there is no feature to be removed further.

Let's plot a correlation matrix between features.

```
corrplot.mixed(cor(train), lower="circle", upper="color",
               tl.pos="lt", diag="n", order="hclust",
hclust.method="complete")
```



A good set of features are visibile when they are highly uncorrelated with each other. The plot above shows average correlation which is not too high, so no further PCA preprocessing is needed.

Modeling

Ran into trouble using Random Forest as my laptop couldn't complete the train function. Switched to XGBOOST instead. It just ran fine in few minutes

```
require(xgboost)

## Loading required package: xgboost
```

```
## Warning: package 'xgboost' was built under R version 3.2.5
```

```
train.matrix = as.matrix(train)
mode(train.matrix) = "numeric"
test.matrix = as.matrix(test)
mode(test.matrix) = "numeric"
# convert outcome from factor to numeric matrix
#   xgboost takes multi-labels in [0, numOfClass)
y = as.matrix(as.integer(outcome)-1)

param <- list("objective" = "multi:softprob",    # multiclass classification
              "num_class" = num.class,    # number of classes
              "eval_metric" = "merror",    # evaluation metric
              "nthread" = 8,   # number of threads to be used
              "max_depth" = 16,    # maximum depth of tree
              "eta" = 0.3,    # step size shrinkage
              "gamma" = 0,    # minimum loss reduction
              "subsample" = 1,    # part of data instances to grow tree
              "colsample_bytree" = 1,  # subsample ratio of columns when
constructing each tree
              "min_child_weight" = 12  # minimum sum of instance weight
needed in a child
              )
set.seed(1234)

system.time( bst.cv <- xgb.cv(param=param, data=train.matrix, label=y,
              nfold=4, nrounds=200, prediction=TRUE, verbose=FALSE) )
```

```
##    user  system elapsed
##  489.08   23.67  171.89
```

```
pred.cv = matrix(bst.cv$pred, nrow=length(bst.cv$pred)/num.class,
ncol=num.class)
pred.cv = max.col(pred.cv, "last")

min.merror.idx = which.min(bst.cv$dt[, test.merror.mean])
min.merror.idx
```

```
## [1] 187
```

```
# minimum merror
bst.cv$dt[min.merror.idx,]
```

```
##    train.merror.mean train.merror.std test.merror.mean test.merror.std
## 1:                 0                0         0.005402        0.000978
```

Model training

Fit the XGBoost gradient boosting model on all of the training data.

```
system.time( bst <- xgboost(param=param, data=train.matrix, label=y,
                           nrounds=min.merror.idx, verbose=0) )
```

```
##    user  system elapsed 
##  146.59    6.58   43.53
```

Predict test data using the trained model

```
pred <- predict(bst, test.matrix)
head(pred, 10)
```

```
##  [1] 2.722199e-04 9.982042e-01 1.132105e-03 1.515472e-04 2.398420e-04
##  [6] 9.991074e-01 6.353945e-04 2.402208e-04 3.893657e-06 1.299460e-05
```

Decoding prediction

```
pred = matrix(pred, nrow=num.class, ncol=length(pred)/num.class)
pred = t(pred)
pred = max.col(pred, "last")
pred.char = toupper(letters[pred])
```

confusion matrix

```
confusionMatrix(factor(y+1), factor(pred.cv))
```

```
## Confusion Matrix and Statistics
## 
##           Reference
## Prediction    1    2    3    4    5
##          1 5566   10    2    2    0
##          2   12 3772   12    0    1
##          3    0   24 3384   14    0
##          4    0    0   19 3194    3
##          5    0    1    1    8 3597
## 
## Overall Statistics
##                                           
##                Accuracy : 0.9944          
##                  95% CI : (0.9933, 0.9954)
##     No Information Rate : 0.2843          
##     P-Value [Acc > NIR] : < 2.2e-16       
##                                           
##                   Kappa : 0.993           
##  Mcnemar's Test P-Value : NA              
## 
## Statistics by Class:
## 
##                      Class: 1 Class: 2 Class: 3 Class: 4 Class: 5
## Sensitivity            0.9978   0.9908   0.9901   0.9925   0.9989
## Specificity            0.9990   0.9984   0.9977   0.9987   0.9994
## Pos Pred Value         0.9975   0.9934   0.9889   0.9932   0.9972
## Neg Pred Value         0.9991   0.9978   0.9979   0.9985   0.9998
## Prevalence             0.2843   0.1940   0.1742   0.1640   0.1835
```

```
## Detection Rate         0.2837   0.1922   0.1725   0.1628   0.1833
## Detection Prevalence   0.2844   0.1935   0.1744   0.1639   0.1838
## Balanced Accuracy      0.9984   0.9946   0.9939   0.9956   0.9991
```

You can see the confusion matrix shows concentration of correct predictions as expected. Hence the average accuracy is 99.44%.

Estimation of the out-of-sample error rate

The testing subset data gives an unbiased estimate of the xgboost algorithm's prediction Accuracy (99.44% as calculated above). The out-of-sample error rate is derived by the formula 100% - Accuracy = 0.66%.

Hence the out-of-sample error rate is 0.66%.

Creating submission files

path <-"" pml_write_files <- function(x) { n <- length(x) for(i in 1: n) { filename <- paste0("problem_id_", i, ".txt") write.table(x[i], file=file.path(path, filename), quote=FALSE, row.names=FALSE, col.names=FALSE) } } pml_write_files(pred.char)