Predicting activity(exercise) quality from activity monitors using machine learning algorithm

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```
## Run time: 2015-08-23 10:08:54
## R version: R version 3.2.0 (2015-04-16)
## OS: Windows 7 x64
```

I. SYNOPSIS:

The purpose of this project is to develop and build a model using machine learning techniques, based on the WLE(Weight Lifting Exercise) Dataset, to predict the manner in which an health participant performed an exercise on 20 different test cases with 'classe' as the ressponse variable.

II. DATASET & DESCRIPTION:

The WLE Dataset is available at http://groupware.les.inf.puc-rio.br/har and was collected from sensors(accelerometers) on the belt, forearm, arm, and dumbell of Six health participants) who 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). Class A corresponds to the specified execution of the exercise, while the other 4 classes correspond to common mistakes.

Training data : https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv Test data : https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv

III. DATA PREPARATION

Read training and test datasets from the source

```r
# read train data set
require(data.table)
```

```
## Loading required package: data.table
```

```r
setInternet2(TRUE)
url <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
pmlTrainData <- fread(url)

# read test data set
url <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"
pmlTestData <- fread(url)
```

IV. EDA & PREDICTOR IDENTIFICATION

Perform an EDA(Exploratory Data Analsysis) on the data set.

```
#summary(pmlTrainData)
#describe(pmlTrainData)
#sapply(pmlTrainData, class)
#str(pmlTrainData)
```

A quick analysis on the test data set shows that we cannot take into all the variables for the prediction and need to identify those predictor variables which are relevant. We are interested in those variables prodcued by sensors with a Non-NA values.

Also subset the primary dataset to include only the predictor candidates and the outcome/response variable - 'classe'.

```
# idenitify predictors
isAnyMissing <- sapply(pmlTestData, function (x) any(is.na(x) | x == ""))
isPredictor <- !isAnyMissing & grepl("belt|[^(fore)]arm|dumbbell|forearm", names(isAnyMissing))
predCandidates <- names(isAnyMissing)[isPredictor]

# subset primary dataset for predictor & outcome variables
varToInclude <- c("classe", predCandidates)
pmlTrainData <- pmlTrainData[, varToInclude, with=FALSE]
```

Perform the required Data Cleansing operations and split the dataset into training and probing dataset in the ratio 60:40. And a final look at the dataset attributes

```
# classe as factor
pmlTrainData <- pmlTrainData[, classe := factor(pmlTrainData[, classe])]
dim(pmlTrainData)
```

```
## [1] 19622    53
```

```
names(pmlTrainData)
```

```
##  [1] "classe"               "roll_belt"            "pitch_belt"
##  [4] "yaw_belt"             "total_accel_belt"     "gyros_belt_x"
##  [7] "gyros_belt_y"         "gyros_belt_z"         "accel_belt_x"
## [10] "accel_belt_y"         "accel_belt_z"         "magnet_belt_x"
## [13] "magnet_belt_y"        "magnet_belt_z"        "roll_arm"
## [16] "pitch_arm"            "yaw_arm"              "total_accel_arm"
## [19] "gyros_arm_x"          "gyros_arm_y"          "gyros_arm_z"
## [22] "accel_arm_x"          "accel_arm_y"          "accel_arm_z"
## [25] "magnet_arm_x"         "magnet_arm_y"         "magnet_arm_z"
## [28] "roll_dumbbell"        "pitch_dumbbell"       "yaw_dumbbell"
## [31] "total_accel_dumbbell" "gyros_dumbbell_x"     "gyros_dumbbell_y"
## [34] "gyros_dumbbell_z"     "accel_dumbbell_x"     "accel_dumbbell_y"
## [37] "accel_dumbbell_z"     "magnet_dumbbell_x"    "magnet_dumbbell_y"
## [40] "magnet_dumbbell_z"    "roll_forearm"         "pitch_forearm"
## [43] "yaw_forearm"          "total_accel_forearm"  "gyros_forearm_x"
## [46] "gyros_forearm_y"      "gyros_forearm_z"      "accel_forearm_x"
## [49] "accel_forearm_y"      "accel_forearm_z"      "magnet_forearm_x"
## [52] "magnet_forearm_y"     "magnet_forearm_z"
```

```
pmlTrainData[, .N, classe]
```

```
##    classe    N
## 1:      A 5580
## 2:      B 3797
## 3:      C 3422
## 4:      D 3216
## 5:      E 3607
```

```
# split dataset [60% - training; 40% - probing]
require(caret)
seed <- as.numeric(as.Date("2015-08-21"))
set.seed(seed)
inTrain <- createDataPartition(pmlTrainData$classe, p=0.6)
trainData <- pmlTrainData[inTrain[[1]]]
probeData <- pmlTrainData[-inTrain[[1]]]
```

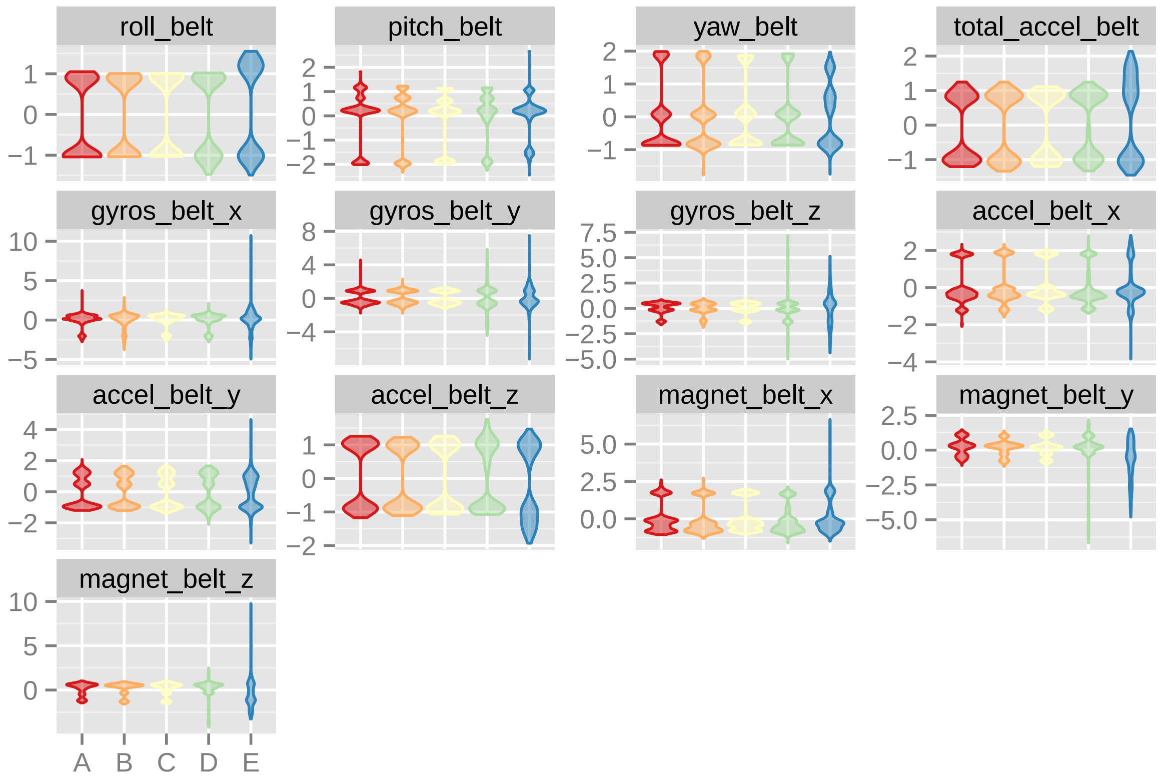
The next step would be to estimate pre-processing transformation (centering, scaling etc) from the training data and applied to probe data set with the same variables. Also diagnose predictors for near zero variance.

```
# preprocess the prediction variables by centering and scaling.
origData <- trainData[, predCandidates, with=FALSE]
preProcessor <- preProcess(origData)
tranformData <- predict(preProcessor, origData)
DTrainCS <- data.table(data.frame(classe = trainData[, classe], tranformData))

# apply the centering and scaling to the probing dataset.
origData <- probeData[, predCandidates, with=FALSE]
tranformData <- predict(preProcessor, origData)
DProbeCS <- data.table(data.frame(classe = probeData[, classe], tranformData))

# check for near zero variance.
nzv <- nearZeroVar(DTrainCS, saveMetrics=TRUE)
if (any(nzv$nzv)) nzv else message("No variables with near zero variance")
```

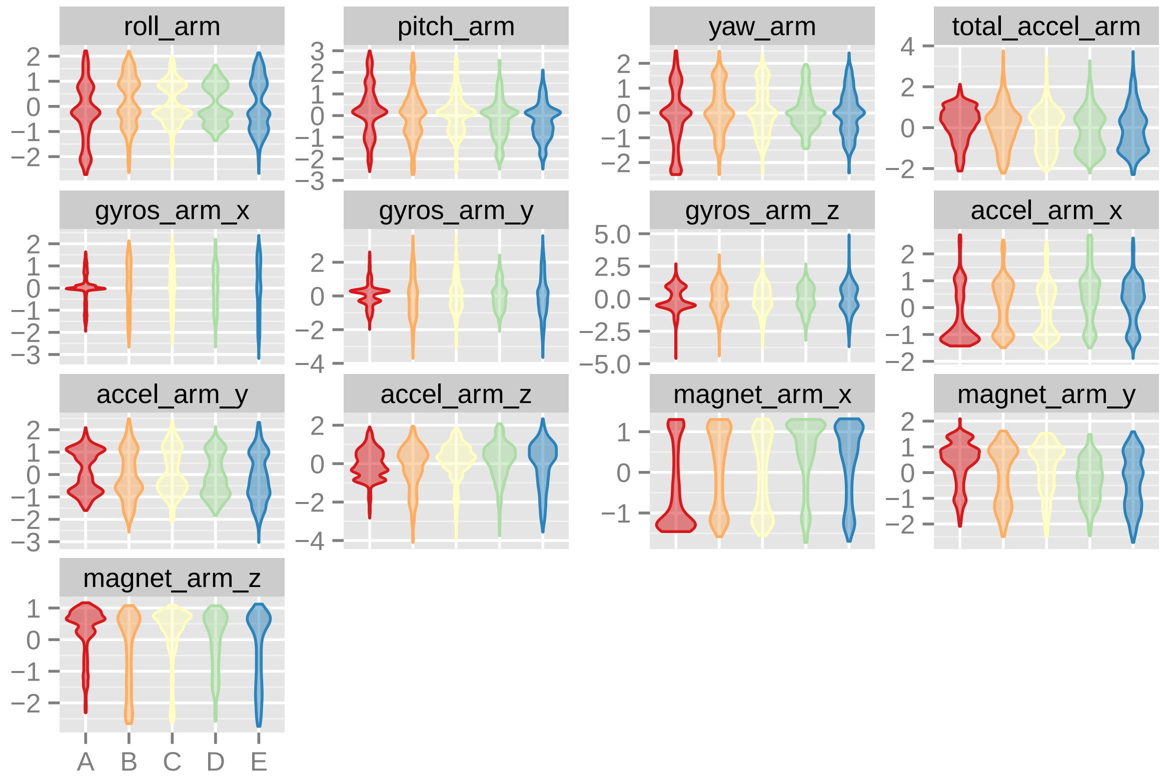
```
## No variables with near zero variance
```

Examine groups of prediction variables and its replationship with response variable using plotting.

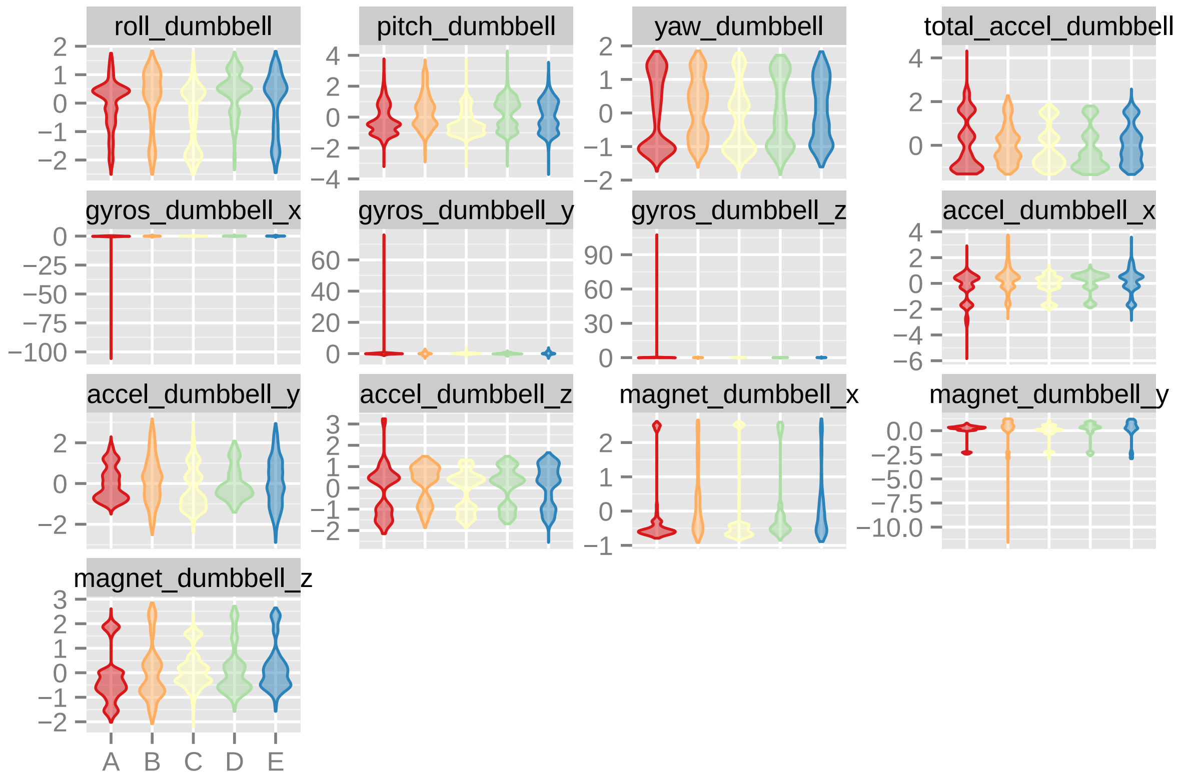
```
require(reshape2)
require(ggplot2)

histGroup <- function (data, regex) {
  col <- grep(regex, names(data))
  col <- c(col, which(names(data) == "classe"))
  n <- nrow(data)
  DMelted <- melt(data[, col, with=FALSE][, rownum := seq(1, n)], id.vars=c("rownum", "classe"))

  ggplot(DMelted, aes(x=classe, y=value)) +
    geom_violin(aes(color=classe, fill=classe), alpha=1/2) +
    facet_wrap(~ variable, scale="free_y") +
    scale_color_brewer(palette="Spectral") +
    scale_fill_brewer(palette="Spectral") +
    labs(x="", y="") +
    theme(legend.position="none")
}

histGroup(DTrainCS, "belt")
```



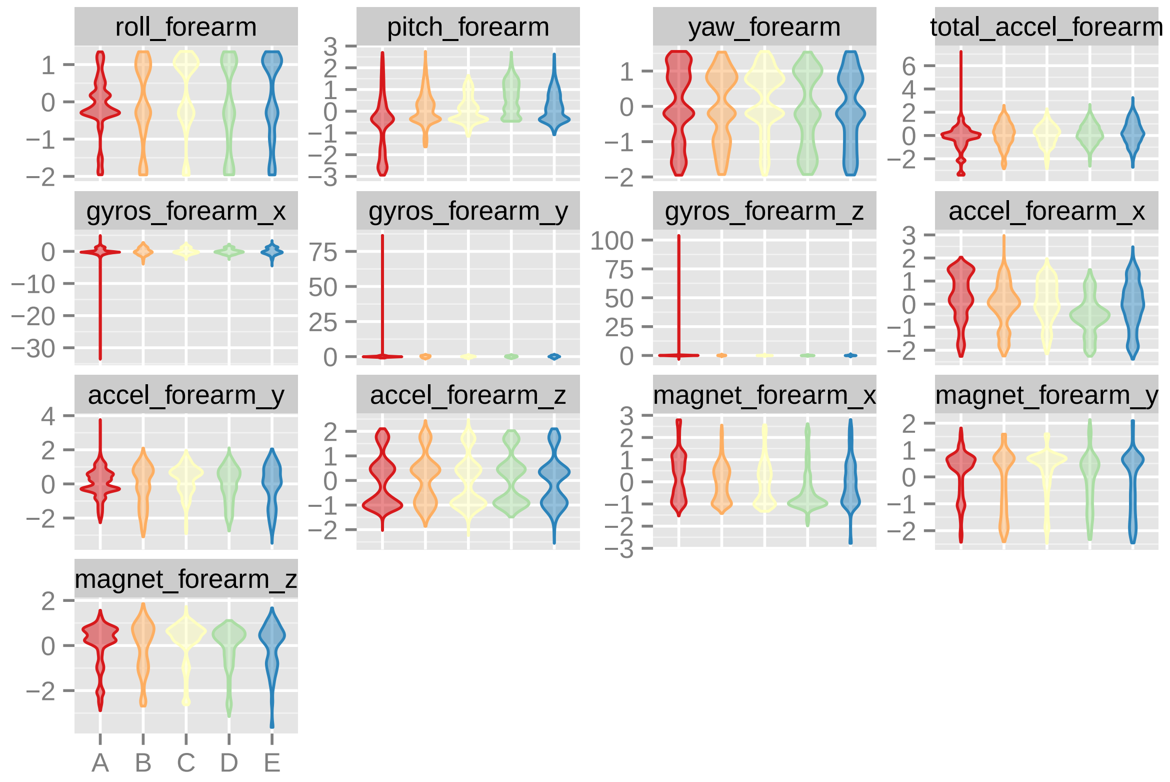
```
histGroup(DTrainCS, "[^(fore)]arm")
```



```r
histGroup(DTrainCS, "dumbbell")
```



```r
histGroup(DTrainCS, "forearm")
```



V. FITTING A MODEL USING RANDOM FOREST

```r
# set up the parallel clusters.
require(parallel)
require(doParallel)
cl <- makeCluster(detectCores() - 1)
registerDoParallel(cl)

# set the control parameters.
ctrl <- trainControl(classProbs=TRUE,
                     savePredictions=TRUE,
                     allowParallel=TRUE)

#fit model (random forrest) over the tuning parameters.
trainingModel <- train(classe ~ ., data=DTrainCS, method="rf")
#system.time(trainingModel <- train(classe ~ ., data=DTrainCS, method="rf"))

# stop the clusters.
stopCluster(cl)
```

VI. OUT-OF SAMPLE ERROR & ERROR ESTIMATE

To evaluate the model we will use the confusionmatrix method and we will focus on accuracy, sensitivity & specificity metrics. As seen from the result of the confusionmatrix below, the model is good and efficient because it has an accuracy of 0.997 and very good sensitivity & specificity values on the testing dataset. (the lowest value is 0.992 for the sensitivity of the class C)

The estimated error rate is less than 1%.

```
# evaluate the model on the training dataset
hat <- predict(trainingModel, DTrainCS)
confusionMatrix(hat, trainData[, classe])
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 3348    0    0    0    0
##          B    0 2279    0    0    0
##          C    0    0 2054    0    0
##          D    0    0    0 1930    0
##          E    0    0    0    0 2165
##
## Overall Statistics
##
##                Accuracy : 1
##                  95% CI : (0.9997, 1)
##     No Information Rate : 0.2843
##     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             0.2843   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2843   0.1935   0.1744   0.1639   0.1838
## Detection Prevalence   0.2843   0.1935   0.1744   0.1639   0.1838
## Balanced Accuracy      1.0000   1.0000   1.0000   1.0000   1.0000
```

```
# final model
varImp(trainingModel)
```

```
## rf variable importance
##
##   only 20 most important variables shown (out of 52)
##
##                      Overall
## roll_belt            100.000
## pitch_forearm         58.461
## yaw_belt              56.369
## pitch_belt            44.804
## magnet_dumbbell_z     43.833
## magnet_dumbbell_y     42.366
## roll_forearm          40.430
## accel_dumbbell_y      20.371
## accel_forearm_x       17.013
## magnet_dumbbell_x     16.001
## roll_dumbbell         15.349
## magnet_forearm_z      14.122
## magnet_belt_z         14.119
## accel_belt_z          13.681
## accel_dumbbell_z      13.672
## total_accel_dumbbell  12.936
## gyros_belt_z          11.067
## yaw_arm               10.852
## magnet_belt_y         10.826
## magnet_belt_x          9.811
```

```
trainingModel$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: 27
##
##         OOB estimate of  error rate: 0.96%
## Confusion matrix:
##      A    B    C    D    E class.error
## A 3342    3    1    0    2 0.001792115
## B   28 2245    5    1    0 0.014918824
## C    0   15 2029   10    0 0.012171373
## D    0    1   31 1896    2 0.017616580
## E    0    1    6    7 2151 0.006466513
```

```
# save training model
save(trainingModel, file="trainingModel.RData")

# Get predictions and evaluate.
DTestCS <- predict(preProcessor, pmlTestData[, predCandidates, with=FALSE])
hat <- predict(trainingModel, DTestCS)
pmlTestData <- cbind(hat , pmlTestData)
subset(pmlTestData, select=names(pmlTestData)[grep("belt|[^(fore)]arm|dumbbell|forearm", names(pmlTestDa
```

VII. PREDICTION ON TEST SET

And the final prediction on the 20 test cases are:

1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 B A B A A E D B A A B C B A E E A B B B