

PML-writeup

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introduction & summary

This report predict the manner in which person performed their exercise, using data from accelerometers on the belt, forearm, arm, and dumbbell of 6 participants. The data for this project come from this source: <http://groupware.les.inf.puc-rio.br/har>.

Data loading and analysis

First loading required packages and data.

```
library(caret)
```

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

Then load data and do some exploratory data analysis. The files can be downloaded from: - <https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv> for training - [https://d396qusza40orc.cloudfront.net/pml-testing.csv](https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv) for testing.

```
train <- read.csv('pml-training.csv' , na.strings=c("NA",""))
test <- read.csv('pml-testing.csv' , na.strings=c("NA",""))
```

```
## explorary data analysis
str(train)
```

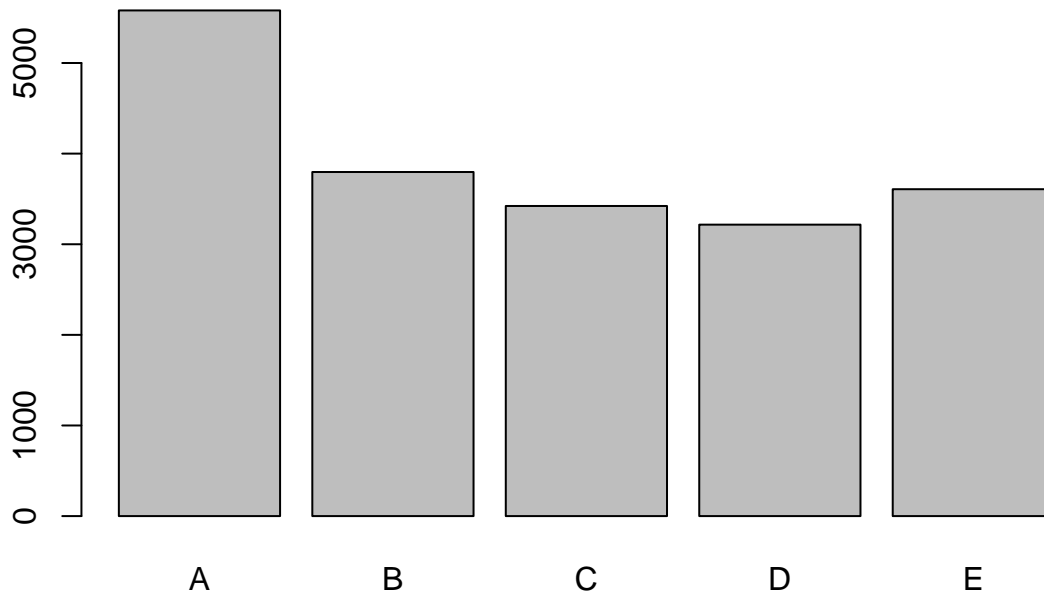
```
## 'data.frame': 19622 obs. of 160 variables:
## $ X : int 1 2 3 4 5 6 7 8 9 10 ...
## $ user_name : Factor w/ 6 levels "adelmo","carlitos",...: 2 2 2 2 2 2 2 2 2 2 ...
## $ raw_timestamp_part_1 : int 1323084231 1323084231 1323084231 1323084232 1323084232 1323084232 ...
## $ raw_timestamp_part_2 : int 788290 808298 820366 120339 196328 304277 368296 440390 484323 484...
## $ cvtd_timestamp : Factor w/ 20 levels "02/12/2011 13:32",...: 9 9 9 9 9 9 9 9 9 9 ...
## $ new_window : Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
## $ num_window : int 11 11 11 12 12 12 12 12 12 12 ...
## $ roll_belt : num 1.41 1.41 1.42 1.48 1.48 1.45 1.42 1.42 1.43 1.45 ...
## $ pitch_belt : num 8.07 8.07 8.07 8.05 8.07 8.06 8.09 8.13 8.16 8.17 ...
## $ yaw_belt : num -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 ...
## $ total_accel_belt : int 3 3 3 3 3 3 3 3 3 3 ...
## $ kurtosis_roll_belt : Factor w/ 396 levels "-0.016850","-0.021024",...: NA NA NA NA NA NA NA NA NA NA ...
## $ kurtosis_pitch_belt : Factor w/ 316 levels "-0.021887","-0.060755",...: NA NA NA NA NA NA NA NA NA NA ...
## $ kurtosis_yaw_belt : Factor w/ 1 level "#DIV/0!": NA NA NA NA NA NA NA NA NA NA ...
## $ skewness_roll_belt : Factor w/ 394 levels "-0.003095","-0.010002",...: NA NA NA NA NA NA NA NA NA NA ...
## $ skewness_roll_belt.1 : Factor w/ 337 levels "-0.005928","-0.005960",...: NA NA NA NA NA NA NA NA NA NA ...
## $ skewness_yaw_belt : Factor w/ 1 level "#DIV/0!": NA NA NA NA NA NA NA NA NA NA ...
## $ max_roll_belt : num NA NA NA NA NA NA NA NA NA NA ...
## $ max_pitch_belt : int NA NA NA NA NA NA NA NA NA NA ...
```

```

## $ max_yaw_belt      : Factor w/ 67 levels "-0.1","-0.2",...: NA NA NA NA NA NA NA NA NA NA ...
## $ min_roll_belt     : num  NA NA NA NA NA NA NA NA NA NA ...
## $ min_pitch_belt    : int  NA NA NA NA NA NA NA NA NA NA ...
## $ min_yaw_belt      : Factor w/ 67 levels "-0.1","-0.2",...: NA NA NA NA NA NA NA NA NA NA ...
## $ amplitude_roll_belt : num  NA NA NA NA NA NA NA NA NA NA ...
## $ amplitude_pitch_belt : int  NA NA NA NA NA NA NA NA NA NA ...
## $ amplitude_yaw_belt : Factor w/ 3 levels "#DIV/0!","0.00",...: NA NA NA NA NA NA NA NA NA NA .
## $ var_total_accel_belt : num  NA NA NA NA NA NA NA NA NA NA ...
## $ avg_roll_belt     : num  NA NA NA NA NA NA NA NA NA NA ...
## $ stddev_roll_belt  : num  NA NA NA NA NA NA NA NA NA NA ...
## $ var_roll_belt     : num  NA NA NA NA NA NA NA NA NA NA ...
## $ avg_pitch_belt    : num  NA NA NA NA NA NA NA NA NA NA ...
## $ stddev_pitch_belt : num  NA NA NA NA NA NA NA NA NA NA ...
## $ var_pitch_belt    : num  NA NA NA NA NA NA NA NA NA NA ...
## $ avg_yaw_belt      : num  NA NA NA NA NA NA NA NA NA NA ...
## $ stddev_yaw_belt   : num  NA NA NA NA NA NA NA NA NA NA ...
## $ var_yaw_belt      : num  NA NA NA NA NA NA NA NA NA NA ...
## $ gyros_belt_x      : num  0 0.02 0 0.02 0.02 0.02 0.02 0.02 0.02 0.03 ...
## $ gyros_belt_y      : num  0 0 0 0 0.02 0 0 0 0 0 ...
## $ gyros_belt_z      : num  -0.02 -0.02 -0.02 -0.03 -0.02 -0.02 -0.02 -0.02 -0.02 0 ...
## $ accel_belt_x      : int  -21 -22 -20 -22 -21 -21 -22 -22 -20 -21 ...
## $ accel_belt_y      : int  4 4 5 3 2 4 3 4 2 4 ...
## $ accel_belt_z      : int  22 22 23 21 24 21 21 21 24 22 ...
## $ magnet_belt_x     : int  -3 -7 -2 -6 -6 0 -4 -2 1 -3 ...
## $ magnet_belt_y     : int  599 608 600 604 600 603 599 603 602 609 ...
## $ magnet_belt_z     : int  -313 -311 -305 -310 -302 -312 -311 -313 -312 -308 ...
## $ roll_arm          : num  -128 -128 -128 -128 -128 -128 -128 -128 -128 -128 ...
## $ pitch_arm         : num  22.5 22.5 22.5 22.1 22.1 22 21.9 21.8 21.7 21.6 ...
## $ yaw_arm           : num  -161 -161 -161 -161 -161 -161 -161 -161 -161 -161 ...
## $ total_accel_arm   : int  34 34 34 34 34 34 34 34 34 34 ...
## $ var_accel_arm     : num  NA NA NA NA NA NA NA NA NA NA ...
## $ avg_roll_arm      : num  NA NA NA NA NA NA NA NA NA NA ...
## $ stddev_roll_arm   : num  NA NA NA NA NA NA NA NA NA NA ...
## $ var_roll_arm      : num  NA NA NA NA NA NA NA NA NA NA ...
## $ avg_pitch_arm     : num  NA NA NA NA NA NA NA NA NA NA ...
## $ stddev_pitch_arm  : num  NA NA NA NA NA NA NA NA NA NA ...
## $ var_pitch_arm     : num  NA NA NA NA NA NA NA NA NA NA ...
## $ avg_yaw_arm       : num  NA NA NA NA NA NA NA NA NA NA ...
## $ stddev_yaw_arm    : num  NA NA NA NA NA NA NA NA NA NA ...
## $ var_yaw_arm       : num  NA NA NA NA NA NA NA NA NA NA ...
## $ gyros_arm_x       : num  0 0.02 0.02 0.02 0 0.02 0 0.02 0.02 0.02 ...
## $ gyros_arm_y       : num  0 -0.02 -0.02 -0.03 -0.03 -0.03 -0.03 -0.02 -0.03 -0.03 ...
## $ gyros_arm_z       : num  -0.02 -0.02 -0.02 0.02 0 0 0 0 -0.02 -0.02 ...
## $ accel_arm_x       : int  -288 -290 -289 -289 -289 -289 -289 -289 -288 -288 ...
## $ accel_arm_y       : int  109 110 110 111 111 111 111 111 109 110 ...
## $ accel_arm_z       : int  -123 -125 -126 -123 -123 -122 -125 -124 -122 -124 ...
## $ magnet_arm_x      : int  -368 -369 -368 -372 -374 -369 -373 -372 -369 -376 ...
## $ magnet_arm_y      : int  337 337 344 344 337 342 336 338 341 334 ...
## $ magnet_arm_z      : int  516 513 513 512 506 513 509 510 518 516 ...
## $ kurtosis_roll_arm : Factor w/ 329 levels "-0.02438","-0.04190",...: NA NA NA NA NA NA NA NA NA NA
## $ kurtosis_pitch_arm : Factor w/ 327 levels "-0.00484","-0.01311",...: NA NA NA NA NA NA NA NA NA NA
## $ kurtosis_yaw_arm   : Factor w/ 394 levels "-0.01548","-0.01749",...: NA NA NA NA NA NA NA NA NA NA
## $ skewness_roll_arm  : Factor w/ 330 levels "-0.00051","-0.00696",...: NA NA NA NA NA NA NA NA NA NA
## $ skewness_pitch_arm : Factor w/ 327 levels "-0.00184","-0.01185",...: NA NA NA NA NA NA NA NA NA NA

```


histogram classe



As we see there are lots of variables with NA's let's remove those columns with more than 10% NA's. Also remove columns related to index, username or timestamp

```
train <- train[,7:160]
test <- test[,7:160]
NoNa <- apply(!is.na(train),2,sum)>(19622-0.1*19622)
train <- train[,NoNa]
test <- test[,NoNa]
dim(train)
```

```
## [1] 19622    54
```

As I was not able to run a model with 19622 observations, so for speed I needed to reduce the training set to only include 45%

```
InTrain <- createDataPartition(y=train$classe, p=0.45,list=FALSE)
trainset <- train[InTrain,]
testset <- train[-InTrain,]
```

For the training we use a 5-fold cross validation. As we already need to reduce the training set, we don't make k greater than 5, in order to avoid the sample set becoming too small.

```
control <- trainControl(method = "cv", number = 5)
```

As boosting and random forest are the most accurate models, we are using both and checking accuracy.

```
#randomforest
set.seed(32333)
fitrf <- train(classe ~ ., data = trainset, method = "rf", proxy=TRUE, trControl=control)
```

```
## Loading required package: randomForest
## randomForest 4.6-10
## Type rfNews() to see new features/changes/bug fixes.
```

```
#gbm
set.seed(32333)
fitb <- train(classe ~ ., data = trainset, method = "gbm", trControl=control, verbose=FALSE)
```

```
## Loading required package: gbm
## Loading required package: survival
## Loading required package: splines
##
## Attaching package: 'survival'
##
## The following object is masked from 'package:caret':
##
##   cluster
##
## Loading required package: parallel
## Loaded gbm 2.1
## Loading required package: plyr
```

```
fitb$finalModel
```

```
## A gradient boosted model with multinomial loss function.
## 150 iterations were performed.
## There were 53 predictors of which 44 had non-zero influence.
```

Let's compare accuracy of both models:

```
results <- data.frame(method = c(fitr$method, fitb$method),
                      accuracy=c( fitrf$results[fitrf$results$mtry %in% fitrf$bestTune,2],
                                   tail(fitb$results[order(fitb$results$Accuracy),],1)$Accuracy)
                      )
results
```

```
##   method accuracy
## 1     rf 0.9933193
## 2    gbm 0.9840356
```

Accuracy of rf model is better so let's use and view the Random forest model.

```
fitrf$finalModel
```

```
##
## Call:
```

```
## randomForest(x = x, y = y, mtry = param$mtry, proxy = TRUE)
##           Type of random forest: classification
##           Number of trees: 500
## No. of variables tried at each split: 27
##
##           OOB estimate of  error rate: 0.51%
## Confusion matrix:
##      A      B      C      D      E  class.error
## A 2510      0      0      0      1 0.0003982477
## B      5 1699      4      1      0 0.0058513751
## C      0      9 1531      0      0 0.0058441558
## D      0      1  13 1433      1 0.0103591160
## E      0      1      0      9 1614 0.0061576355
```

```
predictionsrf <- predict(fitrfr, trainset)
confusionMatrix(predictionsrf ,trainset$classe)
```

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

```
##
##           Reference
## Prediction      A      B      C      D      E
##           A 2511      0      0      0      0
##           B      0 1709      0      0      0
##           C      0      0 1540      0      0
##           D      0      0      0 1448      0
##           E      0      0      0      0 1624
```

```
## Overall Statistics
```

```
##
##           Accuracy : 1
##           95% CI : (0.9996, 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      0.1839
## Detection Rate     0.2843      0.1935      0.1744      0.1639      0.1839
## Detection Prevalence 0.2843      0.1935      0.1744      0.1639      0.1839
## Balanced Accuracy    1.0000      1.0000      1.0000      1.0000      1.0000
```

As we only used part of the training data set for prediction we can use the other part for testing and estimating the out of sample error.

```
predictiontest <- predict(fitr, testset)
confusionMatrix(predictiontest, testset$classe)
```

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

```
##
```

```
##           Reference
```

```
## Prediction   A    B    C    D    E
##           A 3068   11    0    0    0
##           B    1 2073   12    0    1
##           C    0    3 1870   17    0
##           D    0    1    0 1751    7
##           E    0    0    0    0 1975
```

```
##
```

```
## Overall Statistics
```

```
##
```

```
##           Accuracy : 0.9951
##           95% CI : (0.9936, 0.9963)
##           No Information Rate : 0.2844
##           P-Value [Acc > NIR] : < 2.2e-16
```

```
##
```

```
##           Kappa : 0.9938
```

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

```
##
```

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

```
##
```

```
##           Class: A Class: B Class: C Class: D Class: E
## Sensitivity      0.9997  0.9928  0.9936  0.9904  0.9960
## Specificity      0.9986  0.9984  0.9978  0.9991  1.0000
## Pos Pred Value   0.9964  0.9933  0.9894  0.9955  1.0000
## Neg Pred Value   0.9999  0.9983  0.9987  0.9981  0.9991
## Prevalence       0.2844  0.1935  0.1744  0.1639  0.1838
## Detection Rate   0.2843  0.1921  0.1733  0.1623  0.1830
## Detection Prevalence 0.2854  0.1934  0.1752  0.1630  0.1830
## Balanced Accuracy 0.9991  0.9956  0.9957  0.9947  0.9980
```

```
outOfSampleError <- 1-sum(predictiontest == testset$classe)/length(predictiontest)
print(outOfSampleError)
```

```
## [1] 0.004911956
```