Practical Machine Learning Peer Graded Assignment

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Background

Using devices such as Jawbone Up, Nike FuelBand, and Fitbit it 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 project, your goal will be to use data from accelerometers on the belt, forearm, arm, and dumbell of 6 participants. They were asked to perform barbell lifts correctly and incorrectly in 5 different ways. More information is available from the website here: http://groupware.les.inf.puc-rio.br/har (see the section on the Weight Lifting Exercise Dataset).

Data

The training data for this project are available
here: https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv

The test data are available here: https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv

The data for this project come from this source: http://groupware.les.inf.puc-rio.br/har

Load required packages for analysis

```
library(caret)
## Loading required package: lattice
## Loading required package: ggplot2
library(rpart)
library(ggplot2)
library(corrplot)
library(randomForest)
## 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
set.seed(12345)
```

Load data

```
training_raw <- read.csv("pml-training.csv")[,-1]
testing <- read.csv("pml-testing.csv")[,-1]
# check dimension of the training and test dataset
dim(training_raw)
dim(testing)
```

```
## [1] 19622   159
## [1]  20 159
```

Clean data

```
# remove predictors that have many missing/NA values or non-unique values
NZV <- nearZeroVar(training_raw)
training <- training_raw[, -NZV]
testing <- testing[, -NZV]

# remove cases that have many missing/NA values
NaValues <- sapply(training, function(x) mean(is.na(x))) > 0.9
training <- training[, NaValues == "FALSE"]
testing <- testing[, NaValues == "FALSE"]

# remove id and time variables
training <- training[,-c(1:5)]
testing <- testing[,-c(1:5)]

# check dimension of the cleaned up dataset
dim(training)
## [1] 19622    53
dim(testing)
## [1] 20 53
# take a look at the training dataset
head(training)
##   roll_belt pitch_belt yaw_belt total_accel_belt gyros_belt_x gyros_belt_y
## 1     1.41      8.07   -94.4              3       0.00       0.00
## 2     1.41      8.07   -94.4              3       0.02       0.00
## 3     1.42      8.07   -94.4              3       0.00       0.00
## 4     1.48      8.05   -94.4              3       0.02       0.00
## 5     1.48      8.07   -94.4              3       0.02       0.02
## 6     1.45      8.06   -94.4              3       0.02       0.00
##   gyros_belt_z accel_belt_x accel_belt_y accel_belt_z magnet_belt_x
## 1        -0.02         -21          4         22         -3
## 2        -0.02         -22          4         22         -7
## 3        -0.02         -20          5         23         -2
## 4        -0.03         -22          3         21         -6
## 5        -0.02         -21          2         24         -6
## 6        -0.02         -21          4         21          0
##   magnet_belt_y magnet_belt_z roll_arm pitch_arm yaw_arm total_accel_arm
## 1         599         -313    -128     22.5    -161            34
## 2         608         -311    -128     22.5    -161            34
## 3         600         -305    -128     22.5    -161            34
## 4         604         -310    -128     22.1    -161            34
## 5         600         -302    -128     22.1    -161            34
## 6         603         -312    -128     22.0    -161            34
##   gyros_arm_x gyros_arm_y gyros_arm_z accel_arm_x accel_arm_y accel_arm_z
## 1       0.00        0.00       -0.02        -288         109        -123
## 2       0.02       -0.02       -0.02        -290         110        -125
## 3       0.02       -0.02       -0.02        -289         110        -126
```

```
## 4       0.02      -0.03       0.02       -289        111       -123
## 5       0.00      -0.03       0.00       -289        111       -123
## 6       0.02      -0.03       0.00       -289        111       -122
##   magnet_arm_x magnet_arm_y magnet_arm_z roll_dumbbell pitch_dumbbell
## 1         -368         337         516     13.05217     -70.49400
## 2         -369         337         513     13.13074     -70.63751
## 3         -368         344         513     12.85075     -70.27812
## 4         -372         344         512     13.43120     -70.39379
## 5         -374         337         506     13.37872     -70.42856
## 6         -369         342         513     13.38246     -70.81759
##   yaw_dumbbell total_accel_dumbbell gyros_dumbbell_x gyros_dumbbell_y
## 1    -84.87394                  37               0            -0.02
## 2    -84.71065                  37               0            -0.02
## 3    -85.14078                  37               0            -0.02
## 4    -84.87363                  37               0            -0.02
## 5    -84.85306                  37               0            -0.02
## 6    -84.46500                  37               0            -0.02
##   gyros_dumbbell_z accel_dumbbell_x accel_dumbbell_y accel_dumbbell_z
## 1             0.00             -234               47             -271
## 2             0.00             -233               47             -269
## 3             0.00             -232               46             -270
## 4            -0.02             -232               48             -269
## 5             0.00             -233               48             -270
## 6             0.00             -234               48             -269
##   magnet_dumbbell_x magnet_dumbbell_y magnet_dumbbell_z roll_forearm
## 1              -559               293               -65         28.4
## 2              -555               296               -64         28.3
## 3              -561               298               -63         28.3
## 4              -552               303               -60         28.1
## 5              -554               292               -68         28.0
## 6              -558               294               -66         27.9
##   pitch_forearm yaw_forearm total_accel_forearm gyros_forearm_x
## 1         -63.9       -153                  36            0.03
## 2         -63.9       -153                  36            0.02
## 3         -63.9       -152                  36            0.03
## 4         -63.9       -152                  36            0.02
## 5         -63.9       -152                  36            0.02
## 6         -63.9       -152                  36            0.02
##   gyros_forearm_y gyros_forearm_z accel_forearm_x accel_forearm_y
## 1            0.00           -0.02             192             203
## 2            0.00           -0.02             192             203
## 3           -0.02            0.00             196             204
## 4           -0.02            0.00             189             206
## 5            0.00           -0.02             189             206
## 6           -0.02           -0.03             193             203
##   accel_forearm_z magnet_forearm_x magnet_forearm_y magnet_forearm_z
## 1            -215              -17              654              476
## 2            -216              -18              661              473
## 3            -213              -18              658              469
## 4            -214              -16              658              469
## 5            -214              -17              655              473
## 6            -215               -9              660              478
```

```
##   classe
## 1      A
## 2      A
## 3      A
## 4      A
## 5      A
## 6      A
```

Prepare data partition, for later validation

```
inTrain <- createDataPartition(y= training$classe, p = 0.7, list = FALSE)

training <- training[inTrain, ]

crossvalidation <- training[-inTrain, ]
```

Now we can train our models given the preprocess with PCA

```
# decision trees
model_tree <- train(classe~., data = training, method = "rpart")
# print result of model prediction on original training and crossvalidation dataset
predict_training_tree <- predict(model_tree, training)
confusionmatrix_training_tree <- confusionMatrix(predict_training_tree, training$classe)

predict_crossvalidation_tree <- predict(model_tree, crossvalidation)
confusionmatrix_cv_tree <- confusionMatrix(predict_crossvalidation_tree, crossvalidation$classe)

print(confusionmatrix_cv_tree)
## Confusion Matrix and Statistics
##
##          Reference
## Prediction    A    B    C    D    E
##         A 1074  319  345  319  100
##         B   11  276   20  128   91
##         C   67  207  354  259  205
##         D    0    0    0    0    0
##         E    9    0    0    0  326
##
## Overall Statistics
##
##               Accuracy : 0.4939
##                 95% CI : (0.4785, 0.5093)
##    No Information Rate : 0.2825
##    P-Value [Acc > NIR] : < 2.2e-16
##
##                  Kappa : 0.3393
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
```

```
## Sensitivity          0.9251  0.34414  0.49235   0.0000  0.45152
## Specificity          0.6328  0.92443  0.78237   1.0000  0.99734
## Pos Pred Value       0.4979  0.52471  0.32418      NaN  0.97313
## Neg Pred Value       0.9555  0.85324  0.87906   0.8282  0.89510
## Prevalence           0.2825  0.19513  0.17494   0.1718  0.17567
## Detection Rate       0.2613  0.06715  0.08613   0.0000  0.07932
## Detection Prevalence   0.5248  0.12798  0.26569   0.0000  0.08151
## Balanced Accuracy      0.7789  0.63428  0.63736   0.5000  0.72443
```

```
# random forest
model_rf <- train(classe~., data = training, method = "rf")
# print result of model prediction on original training and crossvalidation dataset
predict_training_rf <- predict(model_rf, training)
confusionmatrix_training_rf <- confusionMatrix(predict_training_rf, training$classe)

predict_crossvalidation_rf <- predict(model_rf, crossvalidation)
confusionmatrix_cv_rf <- confusionMatrix(predict_crossvalidation_rf, crossvalidation$classe)

print(confusionmatrix_cv_rf)
```

```
## Confusion Matrix and Statistics
##
##          Reference
## Prediction    A    B    C    D    E
##         A 1161    0    0    0    0
##         B    0  802    0    0    0
##         C    0    0  719    0    0
##         D    0    0    0  706    0
##         E    0    0    0    0  722
##
## Overall Statistics
##
##               Accuracy : 1
##                 95% CI : (0.9991, 1)
##    No Information Rate : 0.2825
##    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           0.2825   0.1951   0.1749   0.1718   0.1757
## Detection Rate       0.2825   0.1951   0.1749   0.1718   0.1757
## Detection Prevalence   0.2825   0.1951   0.1749   0.1718   0.1757
## Balanced Accuracy      1.0000   1.0000   1.0000   1.0000   1.0000
```

Conclusion

The confusionmatrix showed that the accuracy of the random forest models is better than the decision tree model. Therefore, we used this model to predict on the testing dataset.

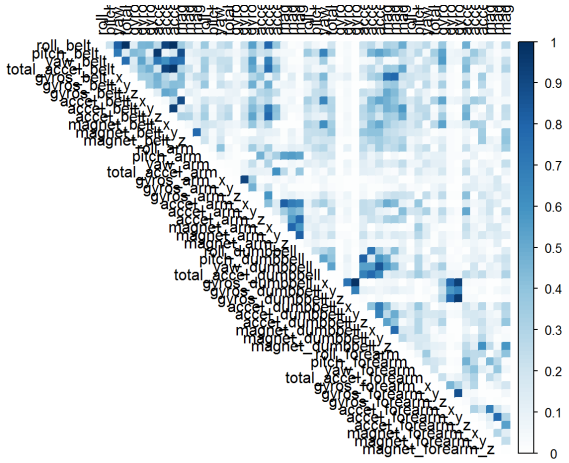
Predict on testing dataset

```
predict_testing <- predict(model_rf, testing)
predict_testing
```

```
##  [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
```

Appendix

```
# explore the remianing predictors
# check the factor variables
predictor_factor <- which(sapply(training, class) == "factor")
# explore correlation between predictors
predictor_cor <- abs(cor(training[,-predictor_factor]))
# turn lower tri to 0
predictor_cor[lower.tri(predictor_cor, diag = TRUE)] <- 0
# visualize result
corrplot(predictor_cor, method  = "color", type = "upper", cl.lim = c(0,1), tl.col = rgb(0, 0, 0))
```




```
# find highly correlated predictors
which(predictor_cor > 0.8, arr.ind = TRUE)
```

```
##                  row col
## roll_belt          1   3
## roll_belt          1   4
## pitch_belt         2   8
## roll_belt          1   9
## total_accel_belt   4   9
## roll_belt          1  10
## total_accel_belt   4  10
## accel_belt_y       9  10
## pitch_belt         2  11
```

```
## accel_belt_x      8  11
## gyros_arm_x       18  19
## accel_arm_x       21  24
## magnet_arm_y      25  26
## gyros_dumbbell_x  31  33
## pitch_dumbbell    28  34
## yaw_dumbbell      29  36
## gyros_dumbbell_x  31  46
## gyros_dumbbell_z  33  46
## gyros_forearm_y   45  46
# Therefore, there are highly correlated predictors, principal component analysis is necessary.
```