Practical Machine Learning - Course Project

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1. Goal

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.

The goal of this project is to predict the manner in which people did the exercise. We will create a report describing how we built our model, how we used cross validation, what we think the expected out of sample error is, and why we made the choices you did. We will also use our prediction model to predict 20 different test cases.

The, in this project we will predict the manner of performing unilateral dumbbell biceps curls based on data from accelerometers on the belt, forearm, arm, and dumbell of 6 participants. The 5 possible methods include -

```
A: exactly according to the specification
B: throwing the elbows to the front
C: lifting the dumbbell only halfway
D: lowering the dumbbell only halfway
E: throwing the hips to the front
```

2. Data Loading and Cleaning

Loading required libraries:

```
#
library(caret)
```

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

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

```
library(rpart)
library(rpart.plot)
library(RColorBrewer)
library(rattle)
```

```
## Loading required package: tibble
```

```
## Loading required package: bitops
```

```
## Rattle: A free graphical interface for data science with R.
## Version 5.4.0 Copyright (c) 2006-2020 Togaware Pty Ltd.
## Type 'rattle()' to shake, rattle, and roll your data.
```

```
library(randomForest)
```

```
## randomForest 4.6-14

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:rattle':
##
##     importance

## The following object is masked from 'package:ggplot2':
##
##     margin
```

```
library(corrplot)
```

```
## corrplot 0.84 loaded
```

```
library(gbm)
```

```
## Loaded gbm 2.1.8
```

We have already downloaded the data. The data is in our working directory.

```
train_in <- read.csv(file = "pml-training.csv", header=T)
valid_in <- read.csv(file="pml-testing.csv", header=T)
dim(train_in)
```

```
## [1] 19622   160
```

```
dim(valid_in)
```

```
## [1]  20 160
```

Now, we clean the data. We are cleaning missing values, variables which have little impact on *classe* and values with near zero variance (NZV).

```
trainData<- train_in[, colSums(is.na(train_in)) == 0]
validData <- valid_in[, colSums(is.na(valid_in)) == 0]

trainData <- trainData[, -c(1:7)]
validData <- validData[, -c(1:7)]

set.seed(1234)
inTrain <- createDataPartition(trainData$classe, p = 0.7, list = FALSE)
```

```
trainData <- trainData[inTrain, ]
testData <- trainData[-inTrain, ]

NZV <- nearZeroVar(trainData)
trainData <- trainData[, -NZV]
testData  <- testData[, -NZV]


dim(trainData)
```

```
## [1] 13737    53
```

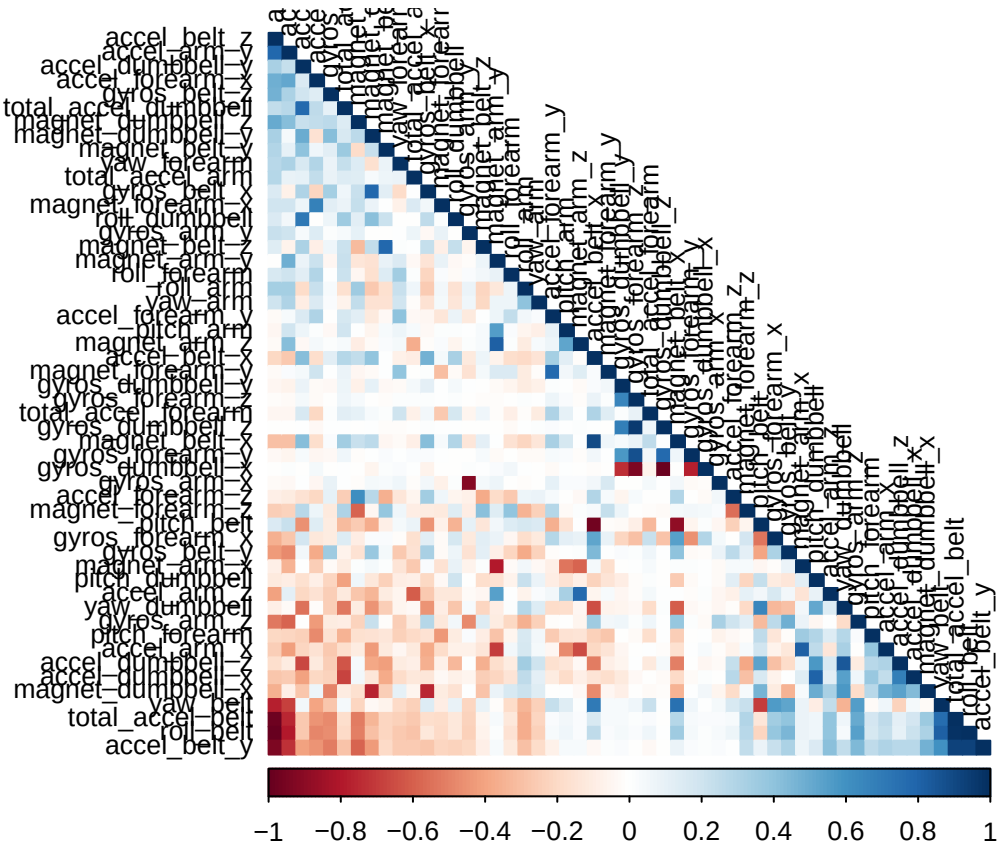
```
dim(testData)
```

```
## [1] 4123   53
```

3. Data Exploration.

To know the relation of variables, we use correlation. The correlated predictors are those with a dark color intersection.

```
cor_mat <- cor(trainData[, -53])
corrplot(cor_mat, order = "FPC", method = "color", type = "lower",tl.cex = 0.8, tl.col = rgb(0, 0, 0))
```



To obtain the names of the variables, we do the following:

```
highlyCorrelated = findCorrelation(cor_mat, cutoff=0.75)

names(trainData)[highlyCorrelated]
```

```
##  [1] "accel_belt_z"      "roll_belt"         "accel_belt_y"
##  [4] "total_accel_belt"  "accel_dumbbell_z"  "accel_belt_x"
##  [7] "pitch_belt"        "magnet_dumbbell_x" "accel_dumbbell_y"
## [10] "magnet_dumbbell_y" "accel_dumbbell_x"  "accel_arm_x"
## [13] "accel_arm_z"       "magnet_arm_y"      "magnet_belt_z"
## [16] "accel_forearm_y"   "gyros_forearm_y"   "gyros_dumbbell_x"
## [19] "gyros_dumbbell_z"  "gyros_arm_x"
```

4. Model Building

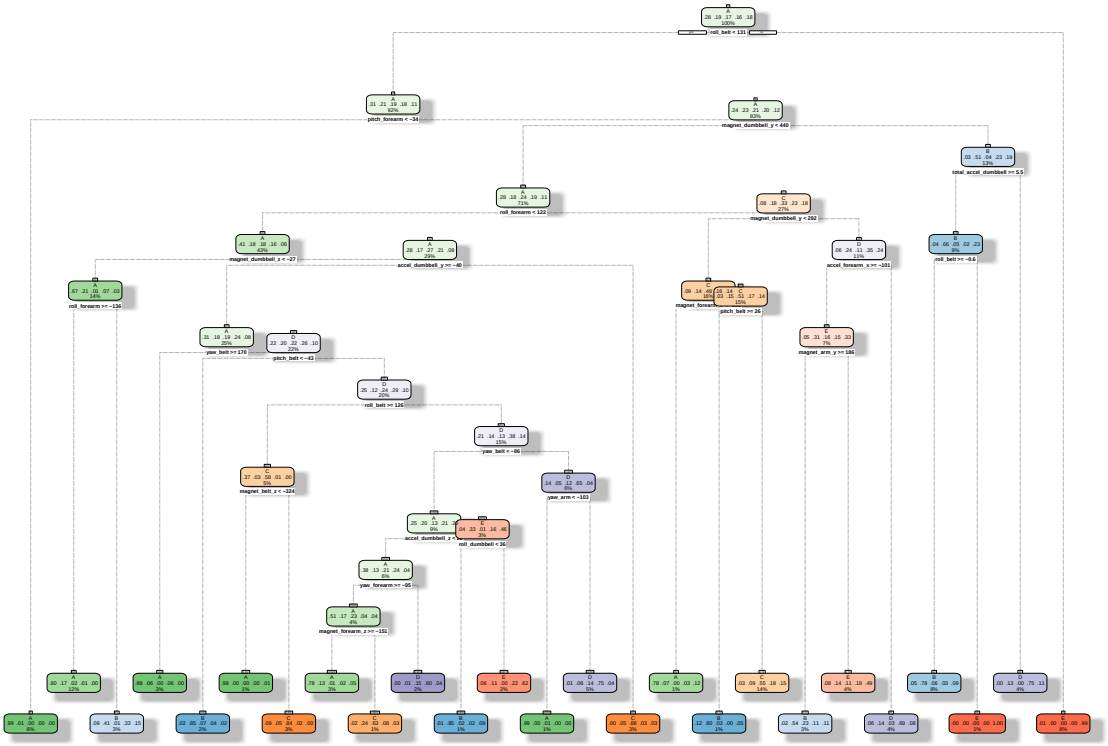
For this project, we will use classification trees, random forest and GBM (generalized boosted models).

4.1 Classification Tree.

We obtain the model and then plot the classification tree.

```
set.seed(12345)
decisionTreeMod1 <- rpart(classe ~ ., data=trainData, method="class")
fancyRpartPlot(decisionTreeMod1)
```

```
## Warning: labs do not fit even at cex 0.15, there may be some overplotting
```



Then, we validate the model on the "test data" to see how well it performs. We can see the accuracy in the *Overall Statistics* section:

```
predictTreeMod1 <- predict(decisionTreeMod1, testData, type = "class")
cmtree <- confusionMatrix(predictTreeMod1, factor(testData$classe))
cmtree
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1067  105    9   24    9
##          B   40  502   59   63   77
##          C   28   90  611  116   86
##          D   11   49   41  423   41
##          E   19   41   18   46  548
##
## Overall Statistics
##
##                Accuracy : 0.7642
##                  95% CI : (0.751, 0.7771)
##     No Information Rate : 0.2826
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.7015
##
```

```
##  Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9159   0.6379   0.8279   0.6295   0.7201
## Specificity            0.9503   0.9284   0.9055   0.9589   0.9631
## Pos Pred Value         0.8789   0.6775   0.6563   0.7487   0.8155
## Neg Pred Value         0.9663   0.9157   0.9602   0.9300   0.9383
## Prevalence             0.2826   0.1909   0.1790   0.1630   0.1846
## Detection Rate         0.2588   0.1218   0.1482   0.1026   0.1329
## Detection Prevalence   0.2944   0.1797   0.2258   0.1370   0.1630
## Balanced Accuracy      0.9331   0.7831   0.8667   0.7942   0.8416
```

4.2 Random Forest

First, we build the model:

```
controlRF <- trainControl(method="cv", number=3, verboseIter=FALSE)
modRF1 <- train(classe ~ ., data=trainData, method="rf", trControl=controlRF)
modRF1$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: 0.7%
## Confusion matrix:
##      A    B    C    D    E class.error
## A 3902    3    0    0    1 0.001024066
## B   19 2634    5    0    0 0.009029345
## C    0   17 2369   10    0 0.011268781
## D    0    1   26 2224    1 0.012433393
## E    0    2    5    6 2512 0.005148515
```

Then, we validate the data on the "test data" to see how well it performs. We can see the accuracy in the *Overall Statistics* section:

```
predictRF1 <- predict(modRF1, newdata=testData)
cmrf <- confusionMatrix(predictRF1, factor(testData$classe))
cmrf
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1165    0    0    0    0
##          B    0  787    0    0    0
##          C    0    0  738    0    0
```

```
##          D    0    0    0  672    0
##          E    0    0    0    0  761
##
## Overall Statistics
##
##                Accuracy : 1
##                  95% CI : (0.9991, 1)
##     No Information Rate : 0.2826
##     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    1.000    1.000   1.0000
## Specificity            1.0000   1.0000    1.000    1.000   1.0000
## Pos Pred Value         1.0000   1.0000    1.000    1.000   1.0000
## Neg Pred Value         1.0000   1.0000    1.000    1.000   1.0000
## Prevalence             0.2826   0.1909    0.179    0.163   0.1846
## Detection Rate         0.2826   0.1909    0.179    0.163   0.1846
## Detection Prevalence   0.2826   0.1909    0.179    0.163   0.1846
## Balanced Accuracy      1.0000   1.0000    1.000    1.000   1.0000
```

4.3 GBM

First, we build the model:

```
set.seed(12345)
controlGBM <- trainControl(method = "repeatedcv", number = 5, repeats = 1)
modGBM  <- train(classe ~ ., data=trainData, method = "gbm", trControl = controlGBM, verbose = FALSE)
modGBM$finalModel
```

```
## A gradient boosted model with multinomial loss function.
## 150 iterations were performed.
## There were 52 predictors of which 52 had non-zero influence.
```

```
print(modGBM)
```

```
## Stochastic Gradient Boosting
##
## 13737 samples
##    52 predictor
##     5 classes: 'A', 'B', 'C', 'D', 'E'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold, repeated 1 times)
## Summary of sample sizes: 10990, 10990, 10989, 10991, 10988
## Resampling results across tuning parameters:
##
```

```
##   interaction.depth  n.trees  Accuracy   Kappa
##   1                   50      0.7521285  0.6858434
##   1                  100      0.8227397  0.7756753
##   1                  150      0.8522224  0.8130469
##   2                   50      0.8564452  0.8181267
##   2                  100      0.9059465  0.8809760
##   2                  150      0.9301168  0.9115592
##   3                   50      0.8969931  0.8695557
##   3                  100      0.9392159  0.9230740
##   3                  150      0.9587251  0.9477728
##
## Tuning parameter 'shrinkage' was held constant at a value of 0.1
##
## Tuning parameter 'n.minobsinnode' was held constant at a value of 10
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were n.trees = 150, interaction.depth =
##  3, shrinkage = 0.1 and n.minobsinnode = 10.
```

Then, we validate the data on the "test data" to see how well it performs. We can see the accuracy in the *Overall Statistics* section:

```
predictGBM <- predict(modGBM, newdata=testData)
cmGBM <- confusionMatrix(predictGBM, factor(testData$classe))
cmGBM
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1155   20    0    0    1
##          B    9  754   17    5    6
##          C    1   12  713   16    3
##          D    0    1    6  647    8
##          E    0    0    2    4  743
##
## Overall Statistics
##
##                Accuracy : 0.9731
##                  95% CI : (0.9677, 0.9778)
##     No Information Rate : 0.2826
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.966
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9914   0.9581   0.9661   0.9628   0.9763
## Specificity            0.9929   0.9889   0.9905   0.9957   0.9982
## Pos Pred Value         0.9821   0.9532   0.9570   0.9773   0.9920
## Neg Pred Value         0.9966   0.9901   0.9926   0.9928   0.9947
## Prevalence             0.2826   0.1909   0.1790   0.1630   0.1846
```

```
## Detection Rate         0.2801   0.1829   0.1729   0.1569   0.1802
## Detection Prevalence   0.2852   0.1919   0.1807   0.1606   0.1817
## Balanced Accuracy      0.9922   0.9735   0.9783   0.9792   0.9873
```

As we can see, Random Forest has the highest Accuracy Rate.

4. Prediction

Finally, we use Random Forest to make the prediction.

```
Results <- predict(modRF1, newdata=validData)
Results
```

```
##  [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
```

Don't forget the meaning: A: exactly according to the specification B: throwing the elbows to the front C: lifting the dumbbell only halfway D: lowering the dumbbell only halfway E: throwing the hips to the front

Thank you!