Machine Learning Assgisnment

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Back Ground

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. The goal of this project is to use data from accelerometers on the belt, forearm, arm, and dumbbell of 6 participants as they perform barbell lifts correctly and incorrectly 5 different ways.

Six young healthy participants were asked to perform one set of 10 repetitions of the Unilateral Dumbbell Biceps Curl in five different fashions: * Class A - exactly according to the specification * Class B - throwing the elbows to the front * Class C - lifting the dumbbell only halfway * Class D - lowering the dumbbell only halfway * Class E - throwing the hips to the front

Class A corresponds to the specified execution of the exercise, while the other 4 classes correspond to common mistakes. Participants were supervised by an experienced weight lifter to make sure the execution complied to the manner they were supposed to simulate. The exercises were performed by six male participants aged between 20-28 years, with little weight lifting experience. Researchers made sure that all participants could easily simulate the mistakes in a safe and controlled manner by using a relatively light dumbbell (1.25kg).

Goal

The goal of this project is to predict the manner in which subjects did the exercise. This is the “classe” variable in the training set. The model will use the other variables to predict with. This report describes: * how the model is built * use of cross validation * an estimate of expected out of sample error

Getting and cleaning the Data

The first step is to download the data, load it into R and prepare it for the modeling process.

Load the functions and static variables

All functions are loaded and static variables are assigned. Also in this section, the seed is set so the pseudo-random number generator operates in a consistent way for repeat-ability.

```
library(caret)
```

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

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

```
library(rpart.plot)
```

```
## Loading required package: rpart
```

```
library(RColorBrewer)
library(rattle)
```

```
## Rattle: A free graphical interface for data science with R.
## Version 5.2.0 Copyright (c) 2006-2018 Togaware Pty Ltd.
## Type 'rattle()' to shake, rattle, and roll your data.
```

```
library(e1071)
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
```

Download Data

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

path <- paste(getwd())
train.file <- file.path(path, "pml-training.csv")
test.file <- file.path(path, "pml-testing.csv")
if (!file.exists(train.file)) {
        download.file(train.url, destfile=train.file)
}
if (!file.exists(test.file)) {
        download.file(test.url, destfile=test.file)
}
```

```
trainRaw  <- read.csv(train.file, na.strings=c("NA","#DIV/0!",""))
testRaw<- read.csv(test.file, na.strings=c("NA","#DIV/0!",""))
dim(trainRaw)
```

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

```
dim(testRaw)
```

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

Clean the data

In this step, we will clean the data and get rid of observations with missing values as well as some meaningless variables.

```
sum(complete.cases(trainRaw))
```

```
## [1] 0
```

First, we remove columns that contain NA missing values.

```
trainRaw <- trainRaw[, colSums(is.na(trainRaw)) == 0]
testRaw <- testRaw[, colSums(is.na(testRaw)) == 0]
```

Next, we get rid of some columns that do not contribute much to the accelerometer measurements.

```
classe <- trainRaw$classe
trainRemove <- grepl("^X|timestamp|window", names(trainRaw))
trainRaw <- trainRaw[, !trainRemove]
trainCleaned <- trainRaw[, sapply(trainRaw, is.numeric)]
trainCleaned$classe <- classe
testRemove <- grepl("^X|timestamp|window", names(testRaw))
testRaw <- testRaw[, !testRemove]
testCleaned <- testRaw[, sapply(testRaw, is.numeric)]
```

Now, the cleaned training data set contains 19622 observations and 53 variables, while the testing data set contains 20 observations and 53 variables. The “classe” variable is still in the cleaned training set.

Slice the data

Then, we can split the cleaned training set into a pure training data set (70%) and a validation data set (30%). We will use the validation data set to conduct cross validation in future steps.

```
set.seed(22519) # For reproducibile purpose
inTrain <- createDataPartition(trainCleaned$classe, p=0.70, list=F)
trainData <- trainCleaned[inTrain, ]
testData <- trainCleaned[-inTrain, ]
```

Data Modeling

We fit a predictive model for activity recognition using Random Forest algorithm because it automatically selects important variables and is robust to correlated covariates & outliers in general. We will use 5-fold cross validation when applying the algorithm.

```
controlRf <- trainControl(method="cv", 5)
modelRf <- train(classe ~ ., data=trainData, method="rf", trControl=controlRf, ntree=
250)
modelRf
```

```
## Random Forest
##
## 13737 samples
##    52 predictor
##     5 classes: 'A', 'B', 'C', 'D', 'E'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 10989, 10991, 10988, 10989, 10991
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa
##    2    0.9909729  0.9885802
##   27    0.9914091  0.9891325
##   52    0.9849311  0.9809363
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 27.
```

Then, we estimate the performance of the model on the validation data set.

```
predictRf <- predict(modelRf, testData)
confusionMatrix(testData$classe, predictRf)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1673    0    0    0    1
##          B    6 1129    4    0    0
##          C    0    0 1021    5    0
##          D    0    0   15  948    1
##          E    0    0    0    6 1076
##
## Overall Statistics
##
##                Accuracy : 0.9935
##                  95% CI : (0.9911, 0.9954)
##     No Information Rate : 0.2853
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9918
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9964   1.0000   0.9817   0.9885   0.9981
## Specificity            0.9998   0.9979   0.9990   0.9968   0.9988
## Pos Pred Value         0.9994   0.9912   0.9951   0.9834   0.9945
## Neg Pred Value         0.9986   1.0000   0.9961   0.9978   0.9996
## Prevalence             0.2853   0.1918   0.1767   0.1630   0.1832
## Detection Rate         0.2843   0.1918   0.1735   0.1611   0.1828
## Detection Prevalence   0.2845   0.1935   0.1743   0.1638   0.1839
## Balanced Accuracy      0.9981   0.9989   0.9903   0.9926   0.9984
```

```
accuracy <- postResample(predictRf, testData$classe)
accuracy
```

```
##  Accuracy     Kappa
## 0.9935429 0.9918320
```

```
oose <- 1 - as.numeric(confusionMatrix(testData$classe, predictRf)$overall[1])
oose
```

```
## [1] 0.006457094
```

So, the estimated accuracy of the model is 99.42% and the estimated out-of-sample error is 0.58%.

Predicting for Test Data Set

Now, we apply the model to the original testing data set downloaded from the data source. We remove the problem_id column first.

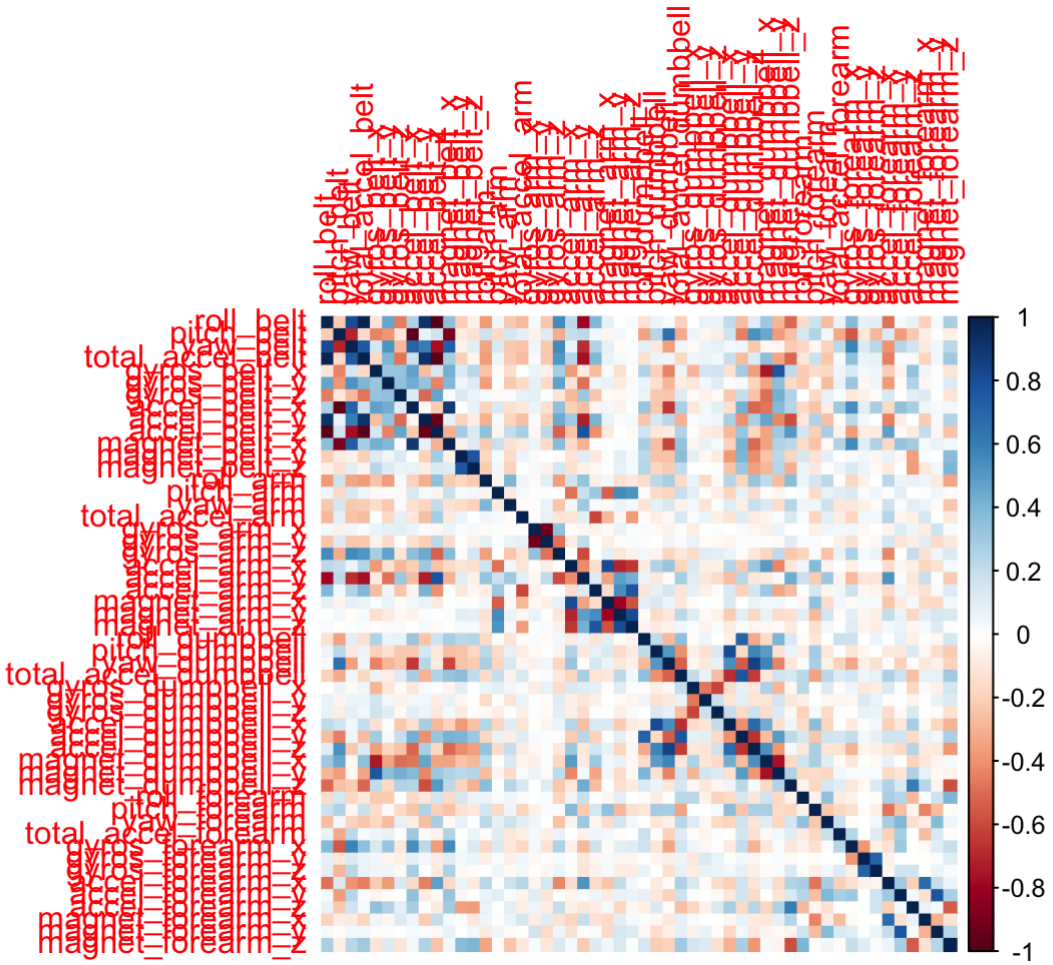
```
result <- predict(modelRf, testCleaned[, -length(names(testCleaned))])
result
```

```
##  [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: Figures

Correlation Matrix Visualization

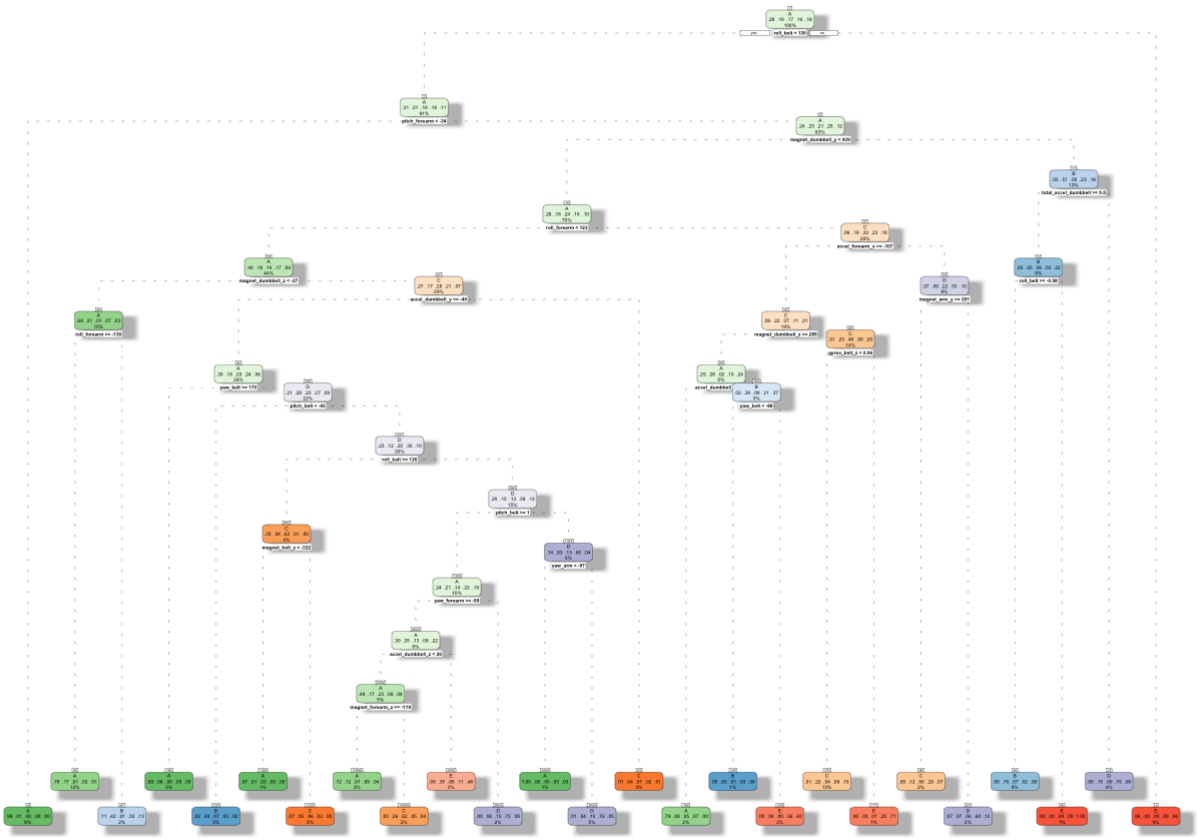
```
corrPlot <- cor(trainData[, -length(names(trainData))])
corrplot(corrPlot, method="color")
```



or

```
treeModel <- rpart(classe ~ ., data=trainData, method="class")
fancyRpartPlot(treeModel)
```

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

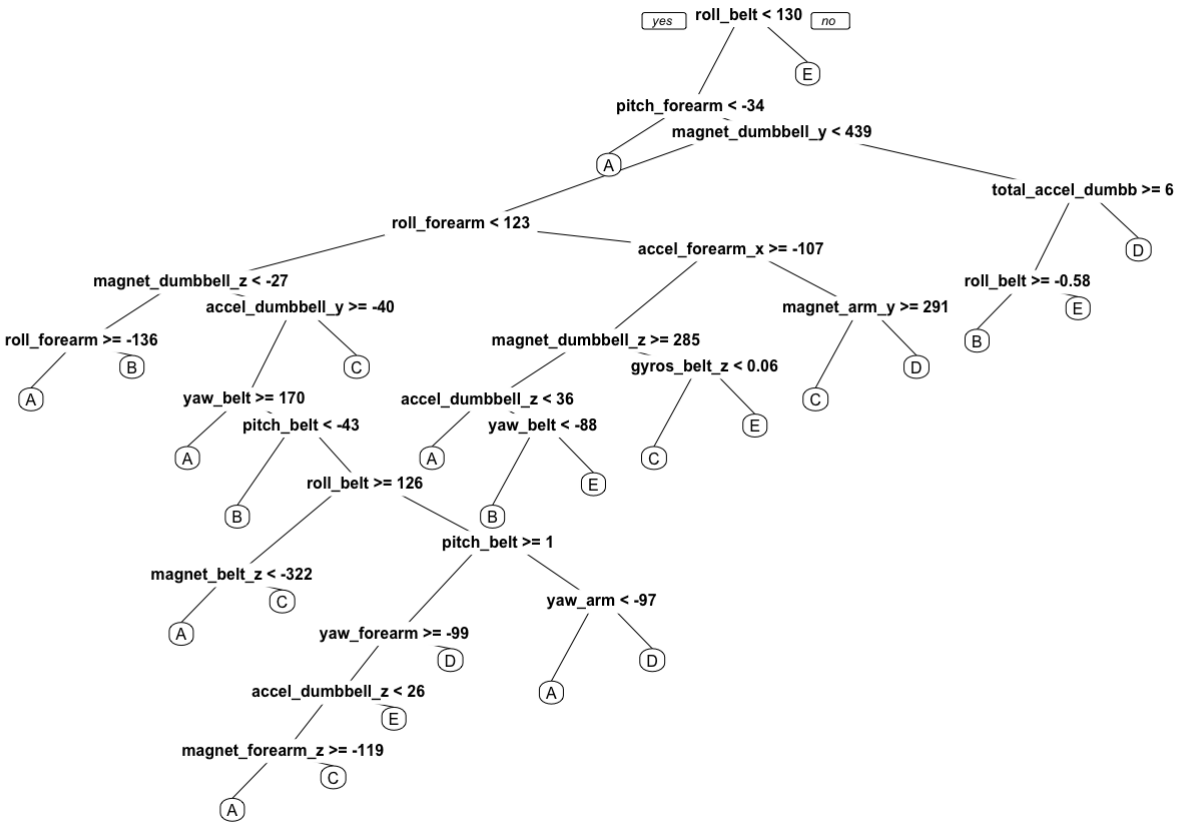


or

Rattle 2019-Jul-17 21:39:45 macbook

fast plot

```
prp(treeModel)
```



##Reference Velloso, E.; Bulling, A.; Gellersen, H.; Ugulino, W.; Fuks, H. Qualitative Activity Recognition of Weight Lifting Exercises. Proceedings of 4th International Conference in Cooperation with SIGCHI (Augmented Human ’13). Stuttgart, Germany: ACM SIGCHI, 2013.