Machine Learning Course Project

Pedro Rojas G

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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

Task

The goal of this project is to predict the manner in which they did the exercise. This is the “classe” variable in the training set. You may use any of the other variables to predict with. You should create a report describing how you built your model, how you used cross validation, what you think the expected out of sample error is, and why you made the choices you did. You will also use your prediction model to predict 20 different test cases.

1. Your submission should consist of a link to a Github repo with your R markdown and compiled HTML file describing your analysis. Please constrain the text of the writeup to < 2000 words and the number of figures to be less than 5. It will make it easier for the graders if you submit a repo with a gh-pages branch so the HTML page can be viewed online (and you always want to make it easy on graders.

2. You should also apply your machine learning algorithm to the 20 test cases available in the test data above. Please submit your predictions in appropriate format to the programming assignment for automated grading. See the programming assignment for additional details.

Data loading and cleaning

```r
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.
```

```r
library(caret)
```

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

```
## Loading required package: ggplot2
## Warning: package 'ggplot2' was built under R version 3.5.3
library(rpart)
library(rpart.plot)
library(corrplot)
## Warning: package 'corrplot' was built under R version 3.5.3
## corrplot 0.84 loaded
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:ggplot2':
##
##     margin
## The following object is masked from 'package:rattle':
##
##     importance
library(RColorBrewer)
```

Now this is test to see if the dataset is downloaded in folder and if not it download it.

```
trainUrl <-"https://d396qusza40orc.cloudfront.net/predmachlearn/pml-train
ing.csv"
testUrl <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testi
ng.csv"
trainFile <- "./data/pml-training.csv"
testFile  <- "./data/pml-testing.csv"
if (!file.exists("./data")) {
  dir.create("./data")
}
if (!file.exists(trainFile)) {
  download.file(trainUrl, destfile = trainFile, method = "curl")
}
if (!file.exists(testFile)) {
  download.file(testUrl, destfile = testFile, method = "curl")
```

```
}
rm(trainUrl)
rm(testUrl)
```

and we now read the data files

```
trainRaw <- read.csv(trainFile)
testRaw <- read.csv(testFile)
dim(trainRaw)
## [1] 19622   160
dim(testRaw)
## [1]  20 160
rm(trainFile)
rm(testFile)
```

the data need some cleaning so we remove missing data points and ignore the varaibles that we are not interested as they are useless in the analysis.

```
NZV <- nearZeroVar(trainRaw, saveMetrics = TRUE)
head(NZV, 20)
##                         freqRatio percentUnique zeroVar   nzv
## X                        1.000000  100.00000000   FALSE FALSE
## user_name                1.100679    0.03057792   FALSE FALSE
## raw_timestamp_part_1     1.000000    4.26562022   FALSE FALSE
## raw_timestamp_part_2     1.000000   85.53154622   FALSE FALSE
## cvtd_timestamp           1.000668    0.10192641   FALSE FALSE
## new_window              47.330049    0.01019264   FALSE  TRUE
## num_window               1.000000    4.37264295   FALSE FALSE
## roll_belt                1.101904    6.77810621   FALSE FALSE
## pitch_belt               1.036082    9.37722964   FALSE FALSE
## yaw_belt                 1.058480    9.97349913   FALSE FALSE
## total_accel_belt         1.063160    0.14779329   FALSE FALSE
## kurtosis_roll_belt    1921.600000    2.02323922   FALSE  TRUE
## kurtosis_picth_belt    600.500000    1.61553358   FALSE  TRUE
## kurtosis_yaw_belt       47.330049    0.01019264   FALSE  TRUE
## skewness_roll_belt    2135.111111    2.01304658   FALSE  TRUE
## skewness_roll_belt.1   600.500000    1.72255631   FALSE  TRUE
```

```
## skewness_yaw_belt      47.330049    0.01019264   FALSE  TRUE
## max_roll_belt           1.000000    0.99378249   FALSE FALSE
## max_picth_belt          1.538462    0.11211905   FALSE FALSE
## max_yaw_belt          640.533333    0.34654979   FALSE  TRUE
training01 <- trainRaw[, !NZV$nzv]
testing01 <- testRaw[, !NZV$nzv]
dim(training01)
## [1] 19622   100
dim(testing01)
## [1]  20 100
rm(trainRaw)
rm(testRaw)
rm(NZV)
```

the variables we are going to remove is that the variables that does not contribute in accelerometer measurements.

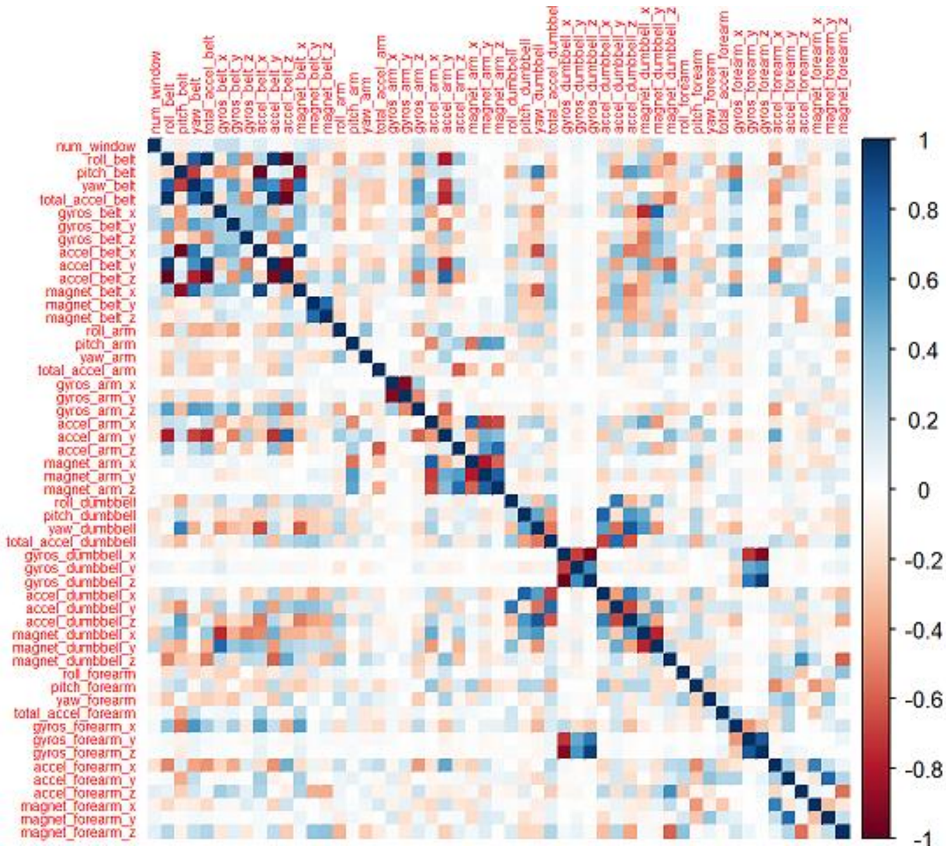
```
regex <- grepl("^X|timestamp|user_name", names(training01))
training <- training01[, !regex]
testing <- testing01[, !regex]
rm(regex)
rm(training01)
rm(testing01)
dim(training)
## [1] 19622    95
dim(testing)
## [1] 20 95
```

and we finally remove NAN

```
cond <- (colSums(is.na(training)) == 0)
training <- training[, cond]
testing <- testing[, cond]
rm(cond)
```

now we visualize the correlation between different variables in the dataset. based on this we can see our ingnorance of variables before if it is ok or not.

```
corrplot(cor(training[, -length(names(training))]), method = "color", tl.
cex = 0.5)
```



Approach

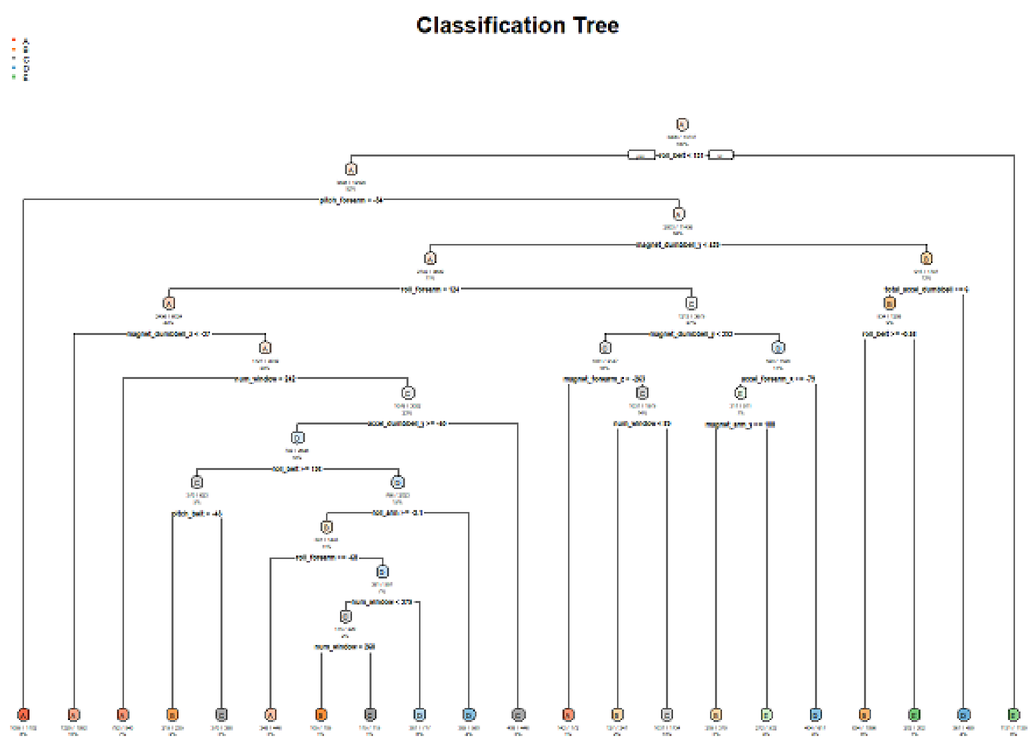
I am going to apply two different models and evaluate how they behave on this data. Two models will be run and they are decision tree and random forest. we seek the model with the highest accuracy will be our final model. we will use the ordinary way to split the cleaned training set into a pure training data set (70%) and a validation data set (30%). We will use the validation data set to conduct cross validation. We are using seed for reproducability purposes.

```
set.seed(56789) # For reproducibile purpose

inTrain <- createDataPartition(training$classe, p = 0.70, list = FALSE)

validation <- training[-inTrain, ]

training <- training[inTrain, ]

rm(inTrain)
```

Decision Tree

we are using decisicon tree to fit our model

```
modelTree <- rpart(classe ~ ., data = training, method = "class")

rpart.plot(modelTree, main="Classification Tree", extra=102, under=TRUE,
faclen=0)
```



Now after we have trained our model, we want to test it against validation data.

```
predictTree <- predict(modelTree, validation, type = "class")

confusionMatrix(validation$classe, predictTree)
```

```
## Confusion Matrix and Statistics
##
##             Reference
## Prediction    A    B    C    D    E
##          A 1526   41   20   61   26
##          B  264  646   74  126   29
##          C   20   56  852   72   26
```

```
##          D   93   31  133  665   42
##          E   82   85   93  128  694
##
## Overall Statistics
##
##                Accuracy : 0.7448
##                  95% CI : (0.7334, 0.7559)
##     No Information Rate : 0.3373
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.6754
##  Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.7688   0.7520   0.7270   0.6321   0.8494
## Specificity            0.9621   0.9019   0.9631   0.9381   0.9234
## Pos Pred Value         0.9116   0.5672   0.8304   0.6898   0.6414
## Neg Pred Value         0.8910   0.9551   0.9341   0.9214   0.9744
## Prevalence             0.3373   0.1460   0.1992   0.1788   0.1388
## Detection Rate         0.2593   0.1098   0.1448   0.1130   0.1179
## Detection Prevalence   0.2845   0.1935   0.1743   0.1638   0.1839
## Balanced Accuracy      0.8654   0.8270   0.8450   0.7851   0.8864
```

```
accuracy <- postResample(predictTree, validation$classe)
ose <- 1 - as.numeric(confusionMatrix(validation$classe, predictTree)$ove
rall[1])
rm(predictTree)
rm(modelTree)
```

We find that the Estimated Accuracy of the Desicion tree Model is 74.4774851% and the Estimated Out-of-Sample Error is about 25.5225149%.

Random forest

We now train our model using random forest and doing the dame validation

```r
modelRF <- train(classe ~ ., data = training, method = "rf", trControl =
trainControl(method = "cv", 5), ntree = 250)

modelRF
```

```
## Random Forest
##
## 13737 samples
##    53 predictor
##     5 classes: 'A', 'B', 'C', 'D', 'E'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 10989, 10990, 10990, 10990, 10989
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa
##    2    0.9949768  0.9936459
##   27    0.9976705  0.9970535
##   53    0.9957051  0.9945672
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 27.
```

Now after we have trained our model, we want to test it against validation data.

```r
predictRF <- predict(modelRF, validation)

confusionMatrix(validation$classe, predictRF)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1674    0    0    0    0
##          B    3 1136    0    0    0
##          C    0    1 1022    3    0
##          D    0    0    4  960    0
##          E    0    0    0    1 1081
##
```

```
## Overall Statistics
##
##                Accuracy : 0.998
##                  95% CI : (0.9964, 0.9989)
##     No Information Rate : 0.285
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9974
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9982   0.9991   0.9961   0.9959   1.0000
## Specificity            1.0000   0.9994   0.9992   0.9992   0.9998
## Pos Pred Value         1.0000   0.9974   0.9961   0.9959   0.9991
## Neg Pred Value         0.9993   0.9998   0.9992   0.9992   1.0000
## Prevalence             0.2850   0.1932   0.1743   0.1638   0.1837
## Detection Rate         0.2845   0.1930   0.1737   0.1631   0.1837
## Detection Prevalence   0.2845   0.1935   0.1743   0.1638   0.1839
## Balanced Accuracy      0.9991   0.9992   0.9976   0.9975   0.9999
```

```
accuracy <- postResample(predictRF, validation$classe)
ose <- 1 - as.numeric(confusionMatrix(validation$classe, predictRF)$overa
ll[1])
rm(predictRF)
```

We find that the Estimated Accuracy of the Random Forest Model is 99.7960918% and the Estimated Out-of-Sample Error is about 0.2039082%.

Conlusion

we find that the Accuracy of the Random Forest Model and error is better than the Decision Tree model. so we conclude that the random forest is the better model.

submission part

this is the code for predicting outcome levels on the original Testing data set using Random Forest algorithm as it is the chosn model as being better at performance on our data.

```r
rm(accuracy)
rm(ose)
predict(modelRF, testing[, -length(names(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
```