Machine Learning Course Project

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9/30/2020

Introduction

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. 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, my goal is 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.

We have analyzed and interpreted our findings with help of machine learning algorithms. We cleaned our data for our analysis for relevant study.

```
library(caret)
## Loading required package: lattice
## Loading required package: ggplot2
library(rpart.plot)
## Loading required package: rpart
library(rpart)
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
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.

## ## Attaching package: 'rattle'

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

training <- read.csv('training_data.csv', na.strings = c("NA", "#DIV/0!", ""))
testing <- read.csv('testing_data.csv', na.strings = c("NA", "#DIV/0!", ""))</pre>
```

Data Cleaning

Step 1: We first remove those columns that has more than 95% of the observation as NA. We will filter out those records.

```
cleancolumn <- colSums(is.na(training))/nrow(training) < 0.95
cleantraining <- training[,cleancolumn]

# Verifying whether we have removed correctly

colSums(is.na(cleantraining))/nrow(cleantraining)</pre>
```

##	Х	user_name	raw_timestamp_part_1
##	0	0	0
##	raw_timestamp_part_2	cvtd_timestamp	new_window
##	0	0	0
##	num_window	roll_belt	pitch_belt
##	0	0	0
##	yaw_belt	total_accel_belt	gyros_belt_x
##	0	0	0
##	gyros_belt_y	gyros_belt_z	accel_belt_x
##	0	0	0
##	accel_belt_y	accel_belt_z	${\tt magnet_belt_x}$
##	0	0	0
##	magnet_belt_y	magnet_belt_z	roll_arm
##	0	0	0
##	pitch_arm	yaw_arm	total_accel_arm
##	0	0	0
##	<pre>gyros_arm_x</pre>	<pre>gyros_arm_y</pre>	gyros_arm_z
##	0	0	0
##	$accel_arm_x$	accel_arm_y	accel_arm_z
##	0	0	0
##	${\tt magnet_arm_x}$	magnet_arm_y	${\tt magnet_arm_z}$
##	0	0	0

```
##
                              pitch_dumbbell
          roll_dumbbell
                                                        yaw_dumbbell
##
   total_accel_dumbbell
                              gyros_dumbbell_x
                                                     gyros_dumbbell_y
##
##
                              accel\_dumbbell\_x
##
       {\tt gyros\_dumbbell\_z}
                                                     accel_dumbbell_y
##
                                                    magnet_dumbbell_y
##
       accel\_dumbbell\_z
                             {\tt magnet\_dumbbell\_x}
##
##
      {\tt magnet\_dumbbell\_z}
                                  roll_forearm
                                                       pitch_forearm
##
                       0
##
            yaw_forearm
                           total_accel_forearm
                                                      gyros_forearm_x
##
##
                               gyros_forearm_z
        gyros_forearm_y
                                                      accel_forearm_x
##
                               accel_forearm_z
##
        accel_forearm_y
                                                     magnet_forearm_x
##
                              magnet_forearm_z
##
                                                                classe
       magnet_forearm_y
##
```

colSums(is.na(cleantraining))

##	X	user_name	<pre>raw_timestamp_part_1</pre>
##	0	0	0
##	raw_timestamp_part_2	$\mathtt{cvtd_timestamp}$	new_window
##	0	0	0
##	${\tt num_window}$	roll_belt	pitch_belt
##	0	0	0
##	yaw_belt	total_accel_belt	gyros_belt_x
##	0	0	0
##	gyros_belt_y	gyros_belt_z	$accel_belt_x$
##	0	0	0
##	accel_belt_y	accel_belt_z	${\tt magnet_belt_x}$
##	0	0	0
##	magnet_belt_y	magnet_belt_z	roll_arm
##	0	0	0
##	pitch_arm	yaw_arm	total_accel_arm
##	0	0	0
##	${ t gyros_arm_x}$	<pre>gyros_arm_y</pre>	${ t gyros_arm_z}$
##	0	0	0
##	$accel_arm_x$	accel_arm_y	accel_arm_z
##	0	0	0
##	${\tt magnet_arm_x}$	magnet_arm_y	${\tt magnet_arm_z}$
##	0	0	0
##	roll_dumbbell	<pre>pitch_dumbbell</pre>	yaw_dumbbell
##	0	0	0
##	total_accel_dumbbell	${ t gyros_dumbbell_x}$	<pre>gyros_dumbbell_y</pre>
##	0	0	0
##	${ t gyros_dumbbell_z}$	accel_dumbbell_x	accel_dumbbell_y
##	0	0	0
##	${\tt accel_dumbbell_z}$	magnet_dumbbell_x	magnet_dumbbell_y
##	0	0	0
##	magnet_dumbbell_z	roll_forearm	<pre>pitch_forearm</pre>
##	0	0	0
##	yaw_forearm	total_accel_forearm	gyros_forearm_x

```
##
                                             0
##
        gyros_forearm_y
                              gyros_forearm_z
                                                     accel_forearm_x
##
                                                                    0
##
        accel_forearm_y
                              accel_forearm_z
                                                    magnet_forearm_x
##
##
       magnet_forearm_y
                                                              classe
                             magnet_forearm_z
##
                                                                    0
```

Step 2:

(i) We will remove unnecessary columns (ii) Partition the training data properly (iii) Will do same for testing data

```
cleantraining <- cleantraining [,-c(1:7)]
cleantest <- testing[,-c(1:7)]
set.seed(34)
inTrainIndex <- caret::createDataPartition(cleantraining$classe,p=0.75,list=FALSE)
trainingdata <- cleantraining[inTrainIndex,]
trainingcrossvalue <- cleantraining[-inTrainIndex,]
allNames <- names(cleantraining)
cleantest <- testing[,allNames[1:52]]</pre>
```

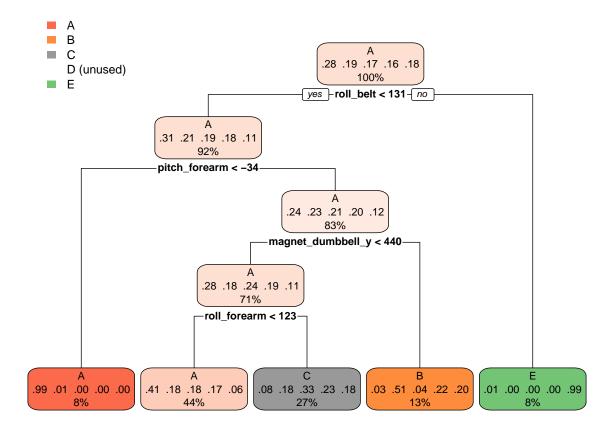
ML Algorithm-Decision Tree

```
decisionTree <- train(classe ~., method='rpart', data=trainingdata)
decisionTreePrediction <- predict(decisionTree, trainingcrossvalue)
trainingcrossvalue$classe <- as.factor(trainingcrossvalue$classe)
confusionMatrix(trainingcrossvalue$classe, decisionTreePrediction)</pre>
```

```
## Confusion Matrix and Statistics
##
##
            Reference
## Prediction
                Α
                      В
                           С
                                D
                     28 102
                                     2
##
           A 1263
                                0
                         248
##
           B 381 320
            С
              411
                     25 419
                                     0
##
                                0
##
           D
               368 143
                         293
                                0
                                     0
##
           E 154 109
                        241
                                0 397
##
## Overall Statistics
##
##
                  Accuracy : 0.4892
##
                    95% CI : (0.4751, 0.5033)
##
       No Information Rate: 0.5255
       P-Value [Acc > NIR] : 1
##
##
##
                     Kappa: 0.3319
##
##
   Mcnemar's Test P-Value : NA
## Statistics by Class:
```

```
##
##
                       Class: A Class: B Class: C Class: D Class: E
## Sensitivity
                         0.4901 0.51200 0.32157
                                                            0.99499
## Specificity
                         0.9433 0.85300
                                          0.87892
                                                    0.8361
                                                            0.88812
## Pos Pred Value
                         0.9054 0.33720
                                          0.49006
                                                        NA
                                                            0.44062
## Neg Pred Value
                         0.6255 0.92288 0.78167
                                                        NA
                                                            0.99950
## Prevalence
                         0.5255 0.12745
                                          0.26570
                                                    0.0000
                                                            0.08136
## Detection Rate
                                                            0.08095
                         0.2575 0.06525
                                          0.08544
                                                    0.0000
## Detection Prevalence
                         0.2845 0.19352
                                          0.17435
                                                    0.1639
                                                            0.18373
## Balanced Accuracy
                         0.7167 0.68250
                                          0.60024
                                                        NA
                                                            0.94156
```

rpart.plot(decisionTree\$finalModel)



ML Algorithm-Random Forest

```
randomforest <- train(classe ~., method='rf', data=trainingdata, ntree=50)
rfPrediction <- predict(randomforest, trainingcrossvalue)
confusionMatrix(trainingcrossvalue$classe, rfPrediction)

## Confusion Matrix and Statistics
##
## Reference</pre>
```

```
## Prediction
                            C
                                 D
                 Α
##
            A 1392
                       1
                                 0
                                       1
                            1
            В
##
                 4
                     943
                                 0
                                       1
            С
                 0
                                       0
##
                       4
                          849
                                 2
##
            D
                  1
                       0
                           12
                               791
                                       0
            Е
                  0
                       0
                            2
                                    898
##
## Overall Statistics
##
##
                  Accuracy : 0.9937
##
                     95% CI: (0.991, 0.9957)
       No Information Rate: 0.2849
##
       P-Value [Acc > NIR] : < 2.2e-16
##
##
##
                      Kappa : 0.992
##
##
    Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##
                         Class: A Class: B Class: C Class: D Class: E
## Sensitivity
                           0.9964
                                    0.9947
                                              0.9815
                                                        0.9962
                                                                 0.9978
## Specificity
                                    0.9985
                                              0.9985
                                                        0.9968
                                                                 0.9993
                           0.9991
## Pos Pred Value
                           0.9978
                                    0.9937
                                              0.9930
                                                        0.9838
                                                                 0.9967
## Neg Pred Value
                           0.9986
                                    0.9987
                                              0.9960
                                                        0.9993
                                                                 0.9995
## Prevalence
                           0.2849
                                    0.1933
                                              0.1764
                                                        0.1619
                                                                 0.1835
## Detection Rate
                           0.2838
                                    0.1923
                                              0.1731
                                                        0.1613
                                                                 0.1831
## Detection Prevalence
                           0.2845
                                    0.1935
                                              0.1743
                                                        0.1639
                                                                 0.1837
                                    0.9966
                                              0.9900
                                                        0.9965
                                                                 0.9985
## Balanced Accuracy
                           0.9978
```

```
predict(randomforest, cleantest)
```

```
## [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
```

Conclusion

We have used two machine learning algorithms. Among them random forest worked much better than the other one. So inspite of decision tree algorithm, we should use randomforest algorithm.