

# Practical Machine Learning

Ruben\_Mkrtchyan

18/05/2021

## Practical Machine Learning

### Peer-Graded Assignment

#### Ruben Mkrtchyan

##### I. Overview

This report is the final assignment for Coursera's Practical Machine Learning course. This course is a part of the Data Science Specialization track which is organized by John Hopkins University. This report will be graded by peers of the same course.

The report will use data from accelerometers on forearm, arm, belt and dumbel of six participants. The data consists of a training data and a test data, which is for validating the selected model. The goal of the report is to predict the way that the participants performed the excercise. That is the "classe" variable in the training set. There will be three models trained in this report, those are: Decision Tree, Random Forest and Gradient Boosted Trees. The best model will be sellected based on the accuracy rate and out of sample error rate. By the use of the selected model, the twenty test cases available in the test data will be predicted.

##### II. 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).

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>

### III.Data Loading, preprocessing and cleaning

#### a)Data Preprocessing and package instalation:

At first, we need to upload the necessary libraries.

```
#install.packages('caret', dependencies = TRUE)
#install.packages('gtable', dependencies = TRUE)
#install.packages('ggplot2', dependencies = TRUE)
#install.packages('gower', dependencies = TRUE)

#install.packages('jquerylib', dependencies = TRUE)

library(caret)

## Warning: package 'caret' was built under R version 4.0.5

## Loading required package: lattice

## Loading required package: ggplot2

## Warning: package 'ggplot2' was built under R version 4.0.5

library(lattice)
library(ggplot2)
library(corrplot)

## Warning: package 'corrplot' was built under R version 4.0.5

## corrplot 0.88 loaded

library(knitr)
library(rpart)
library(rpart.plot)

## Warning: package 'rpart.plot' was built under R version 4.0.5

library(rattle)

## Warning: package 'rattle' was built under R version 4.0.5

## Loading required package: tibble

## Loading required package: bitops

## Warning: package 'bitops' was built under R version 4.0.5
```

```
## 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)

## Warning: package 'randomForest' was built under R version 4.0.5

## 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

set.seed(404) #Setting the seed
```

## b)Data Reading:

Now we read the data.

```
Url_train <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-
training.csv"
Url_test  <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-
testing.csv"

train_data <- read.csv(url(Url_train))
test_data  <- read.csv(url(Url_test))

inTrain <- createDataPartition(train_data$classe, p=0.7, list=FALSE)
Train_Set <- train_data[inTrain, ]
Test_Set  <- train_data[-inTrain, ]
```

Let's check the number of variables of Train\_Set and Test\_Set.

```
dim(Train_Set)

## [1] 13737  160

dim(Test_Set)

## [1] 5885  160
```

As we see, we have got 160 initial variables, however after data cleaning the number will be reduced.

### c)Data Cleaning:

We need to remove the near zero variance (NZV) variables.

```
NZV <- nearZeroVar(Train_Set)
Train_Set <- Train_Set[, -NZV]
Test_Set <- Test_Set[, -NZV]

dim(Train_Set)

## [1] 13737 105

dim(Test_Set)

## [1] 5885 105
```

As we see, the number of variables are reduced to 105 for both Test\_Set and Train\_Set.

Now, we need to clean the variables with mostly NA values.

```
NA_val <- sapply(Train_Set, function(x) mean(is.na(x))) > 0.8
Train_Set <- Train_Set[, NA_val==FALSE]
Test_Set <- Test_Set[, NA_val==FALSE]

dim(Train_Set)

## [1] 13737 59

dim(Test_Set)

## [1] 5885 59
```

Let's check the remaining variables in the reduced sets.

```
head(Test_Set)

##      X user_name raw_timestamp_part_1 raw_timestamp_part_2 cvtd_timestamp
## 5    5 carlitos      1323084232      196328 05/12/2011 11:23
## 7    7 carlitos      1323084232      368296 05/12/2011 11:23
## 8    8 carlitos      1323084232      440390 05/12/2011 11:23
## 13   13 carlitos      1323084232      560359 05/12/2011 11:23
## 14   14 carlitos      1323084232      576390 05/12/2011 11:23
## 22   22 carlitos      1323084232      892313 05/12/2011 11:23
##      num_window roll_belt pitch_belt yaw_belt total_accel_belt gyros_belt_x
## 5           12     1.48     8.07    -94.4           3         0.02
## 7           12     1.42     8.09    -94.4           3         0.02
## 8           12     1.42     8.13    -94.4           3         0.02
## 13          12     1.42     8.20    -94.4           3         0.02
## 14          12     1.42     8.21    -94.4           3         0.02
## 22          12     1.57     8.09    -94.4           3         0.02
##      gyros_belt_y gyros_belt_z accel_belt_x accel_belt_y accel_belt_z
## 5         0.02      -0.02      -21           2          24
## 7         0.00      -0.02      -22           3          21
```

```

## 8      0.00      -0.02      -22      4      21
## 13     0.00      0.00      -22      4      21
## 14     0.00     -0.02     -22      4      21
## 22     0.02     -0.02     -21      3      21
## magnet_belt_x magnet_belt_y magnet_belt_z roll_arm pitch_arm yaw_arm
## 5      -6      600      -302     -128     22.1    -161
## 7      -4      599      -311     -128     21.9    -161
## 8      -2      603      -313     -128     21.8    -161
## 13     -3      606      -309     -128     21.4    -161
## 14     -8      598      -310     -128     21.4    -161
## 22     -2      604      -313     -129     20.8    -161
## total_accel_arm gyros_arm_x gyros_arm_y gyros_arm_z accel_arm_x
accel_arm_y
## 5      34      0.00     -0.03      0.00     -289
111
## 7      34      0.00     -0.03      0.00     -289
111
## 8      34      0.02     -0.02      0.00     -289
111
## 13     34      0.02     -0.02     -0.02     -287
111
## 14     34      0.02      0.00     -0.03     -288
111
## 22     34      0.03     -0.02     -0.02     -289
111
## accel_arm_z magnet_arm_x magnet_arm_y magnet_arm_z roll_dumbbell
## 5     -123     -374      337      506     13.37872
## 7     -125     -373      336      509     13.12695
## 8     -124     -372      338      510     12.75083
## 13     -124     -372      338      509     13.38246
## 14     -124     -371      331      523     13.41048
## 22     -123     -372      338      510     13.37872
## pitch_dumbbell yaw_dumbbell total_accel_dumbbell gyros_dumbbell_x
## 5     -70.42856 -84.85306      37      0.00
## 7     -70.24757 -85.09961      37      0.00
## 8     -70.34768 -85.09708      37      0.00
## 13     -70.81759 -84.46500      37      0.00
## 14     -70.99594 -84.28005      37      0.02
## 22     -70.42856 -84.85306      37      0.00
## gyros_dumbbell_y gyros_dumbbell_z accel_dumbbell_x accel_dumbbell_y
## 5     -0.02      0.00     -233      48
## 7     -0.02      0.00     -232      47
## 8     -0.02      0.00     -234      46
## 13     -0.02     -0.02     -234      48
## 14     -0.02     -0.02     -234      48
## 22     -0.02      0.00     -233      48
## accel_dumbbell_z magnet_dumbbell_x magnet_dumbbell_y magnet_dumbbell_z
## 5     -270     -554      292     -68
## 7     -270     -551      295     -70
## 8     -272     -555      300     -74

```

```

## 13      -269      -552      302      -69
## 14      -268      -554      295      -68
## 22      -270      -554      301      -65
##      roll_forearm pitch_forearm yaw_forearm total_accel_forearm
gyros_forearm_x
## 5      28.0      -63.9      -152      36
0.02
## 7      27.9      -63.9      -152      36
0.02
## 8      27.8      -63.8      -152      36
0.02
## 13     27.2      -63.9      -151      36
0.00
## 14     27.2      -63.9      -151      36
0.00
## 22     27.0      -63.9      -151      36
0.02
##      gyros_forearm_y gyros_forearm_z accel_forearm_x accel_forearm_y
## 5      0.00      -0.02      189      206
## 7      0.00      -0.02      195      205
## 8     -0.02      0.00      193      205
## 13     0.00      -0.03      193      205
## 14     -0.02      -0.03      193      202
## 22     -0.03      -0.02      191      206
##      accel_forearm_z magnet_forearm_x magnet_forearm_y magnet_forearm_z
classe
## 5      -214      -17      655      473
A
## 7      -215      -18      659      470
A
## 8      -213      -9      660      474
A
## 13     -215      -15      655      472
A
## 14     -214      -14      659      478
A
## 22     -213      -17      654      478
A

```

As we see, the first five variables are just identification variables, so we need to clean those too.

```

Train_Set <- Train_Set[, -(1:5)]
Test_Set  <- Test_Set[, -(1:5)]

dim(Train_Set)

## [1] 13737    54

dim(Test_Set)

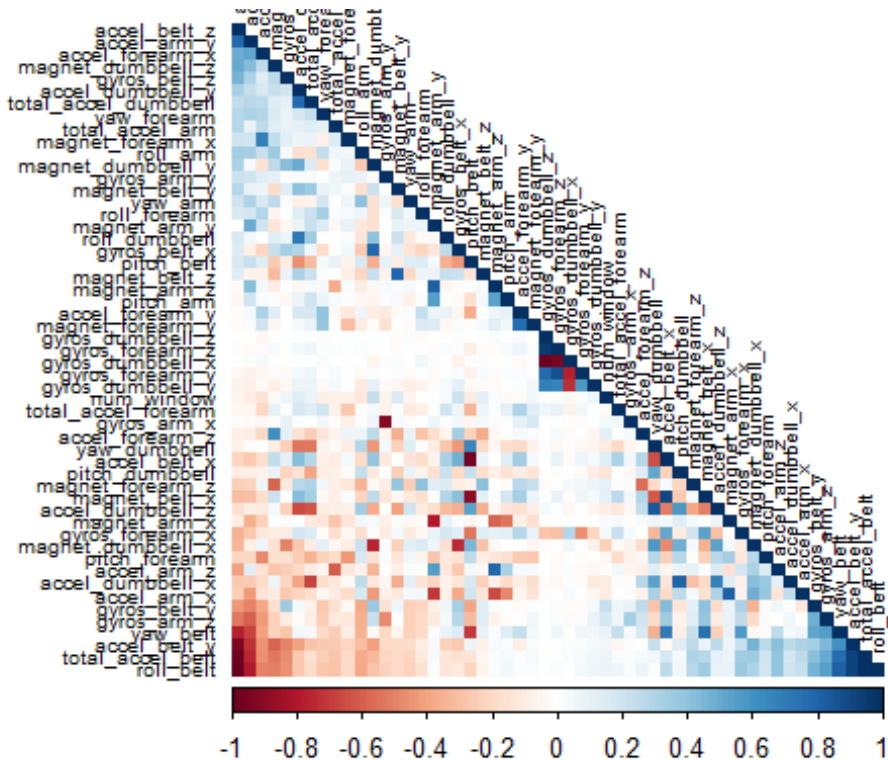
```

```
## [1] 5885 54
```

So, after removing mostly NA variables, NZV variables and the first five identification variables we are left to 54 final variables.

#### d)Correlation Analysis

```
correlation_matrix <- cor(Train_Set[, -54])  
corrplot(correlation_matrix, order = "FPC", method = "color", type = "lower",  
         tl.cex = 0.6, tl.col = rgb(0, 0, 0))
```



Here, in the correlation matrix, the red and blue colors are associated with -1 and 1 correlation respectively. The bright colors show small amount of correlations between the remaining 54 variables.

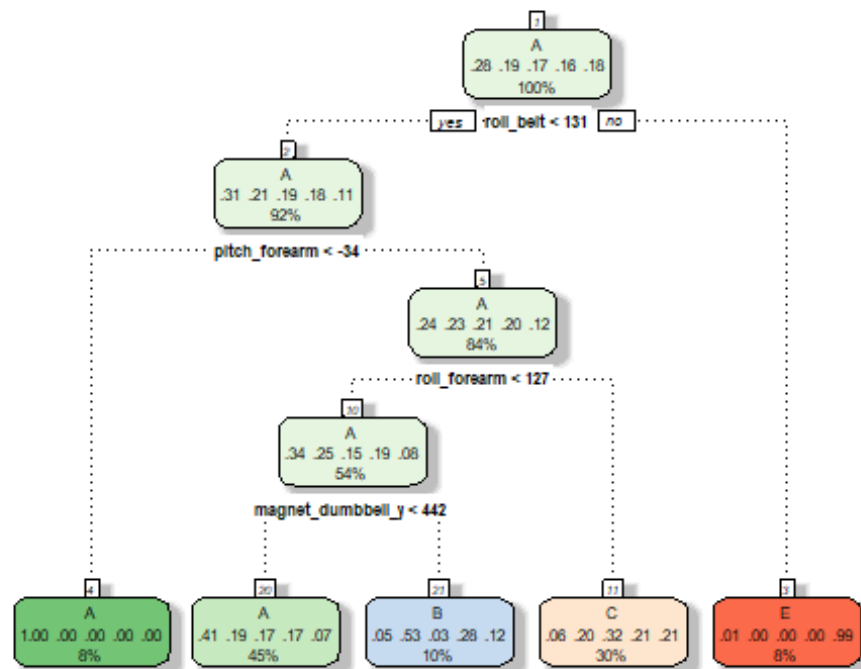
## IV.Buliding and Testing the Models

### a)Model 1:Decision Tree

#### i) The Model

The first model that we will use is Decision Trees. At first we need to get the model, then we use fancyRpartPlot() function to plot the classification tree.

```
control_var <- trainControl(method="cv", number=3, verboseIter=F)  
DT_Model <- train(classe~., data=Test_Set, method="rpart", trControl =  
control_var, tuneLength = 3)  
fancyRpartPlot(DT_Model$finalModel)
```



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#### ii) The

prediction

Now that we already have the model, we need to validate it on Train\_Set.

```

TS_Factored <- factor(Train_Set$classe)
DT_Prediction <- predict(DT_Model, Train_Set)
cmtree <- confusionMatrix(DT_Prediction, TS_Factored)
cmtree

```

## Confusion Matrix and Statistics

##

## Reference

## Prediction A B C D E

## A 3571 1162 1164 1028 358

## B 47 636 35 383 137

## C 280 860 1197 841 878

## D 0 0 0 0 0

## E 8 0 0 0 1152

##

## Overall Statistics

##

## Accuracy : 0.4773

## 95% CI : (0.4689, 0.4856)

## No Information Rate : 0.2843

## P-Value [Acc > NIR] : < 2.2e-16

##

## Kappa : 0.3165

##



```
## McNemar's Test P-Value : NA
##
## Statistics by Class:
##
##           Class: A Class: B Class: C Class: D Class: E
## Sensitivity      0.9142  0.23928  0.49958  0.0000  0.45624
## Specificity      0.6224  0.94566  0.74791  1.0000  0.99929
## Pos Pred Value   0.4903  0.51373  0.29512    NaN  0.99310
## Neg Pred Value   0.9481  0.83823  0.87615  0.8361  0.89083
## Prevalence       0.2843  0.19349  0.17442  0.1639  0.18381
## Detection Rate   0.2600  0.04630  0.08714  0.0000  0.08386
## Detection Prevalence 0.5302  0.09012  0.29526  0.0000  0.08444
## Balanced Accuracy 0.7683  0.59247  0.62374  0.5000  0.72776
```

As we see, the accuracy rate is 0.4773 and the out of sample error rate is  $1 - \text{accuracy} = 0.5227$

## b) Model 2: Random Forest

### i) The Model

Our second model is Random Forest.

```
control_RF <- trainControl(method="cv", number=3, verboseIter=FALSE)
RF_Model <- train(classe ~ ., data=Train_Set, method="rf",
trControl=control_RF)
RF_Model$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: 0.26%
## Confusion matrix:
##      A    B    C    D    E class.error
## A 3904     1     0     0     1 0.0005120328
## B   10 2644     4     0     0 0.0052671181
## C     0     5 2391     0     0 0.0020868114
## D     0     0     7 2244     1 0.0035523979
## E     0     1     0     6 2518 0.0027722772
```

### ii) The prediction

```
#RF <- train(classe~., data=Train_Set, method="rf", trControl = control_var)
RF_Prediction <- predict(RF_Model, Train_Set)
cmrf <- confusionMatrix(RF_Prediction, TS_Factored)
cmrf
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##           A 3906    0    0    0    0
##           B    0 2658    0    0    0
##           C    0    0 2396    0    0
##           D    0    0    0 2252    0
##           E    0    0    0    0 2525
##
## Overall Statistics
##
##           Accuracy : 1
##           95% CI : (0.9997, 1)
##           No Information Rate : 0.2843
##           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       0.2843  0.1935  0.1744  0.1639  0.1838
## Detection Rate   0.2843  0.1935  0.1744  0.1639  0.1838
## Detection Prevalence 0.2843  0.1935  0.1744  0.1639  0.1838
## Balanced Accuracy 1.0000  1.0000  1.0000  1.0000  1.0000
```

The validation test shows that the accuracy rate is 1 and therefore the out of sample error rate will be 0 or something very close to it. Maybe the accuracy is 1 because of overfitting.

## b)Model 3:Generalized Boosted Model (GBM)

### i) The Model

We already have a model which has an accuracy rate of 1, however we still perform the training of the third model which is GBM, Generalized Boosted Model.

```
control_GBM <- trainControl(method = "repeatedcv", number = 5, repeats = 1)
GBM_Model <- train(classe ~ ., data=Train_Set, method = "gbm", trControl =
control_GBM)

## Iter    TrainDeviance    ValidDeviance    StepSize    Improve
##      1         1.6094             nan      0.1000     0.1291
##      2         1.5252             nan      0.1000     0.0886
##      3         1.4658             nan      0.1000     0.0645
```

##	4	1.4219	nan	0.1000	0.0552
##	5	1.3860	nan	0.1000	0.0440
##	6	1.3571	nan	0.1000	0.0447
##	7	1.3289	nan	0.1000	0.0376
##	8	1.3049	nan	0.1000	0.0340
##	9	1.2804	nan	0.1000	0.0302
##	10	1.2589	nan	0.1000	0.0311
##	20	1.0955	nan	0.1000	0.0186
##	40	0.9117	nan	0.1000	0.0092
##	60	0.8003	nan	0.1000	0.0049
##	80	0.7212	nan	0.1000	0.0047
##	100	0.6581	nan	0.1000	0.0042
##	120	0.6034	nan	0.1000	0.0024
##	140	0.5571	nan	0.1000	0.0022
##	150	0.5340	nan	0.1000	0.0025
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1799
##	2	1.4877	nan	0.1000	0.1349
##	3	1.3997	nan	0.1000	0.0990
##	4	1.3351	nan	0.1000	0.0886
##	5	1.2780	nan	0.1000	0.0686
##	6	1.2336	nan	0.1000	0.0701
##	7	1.1879	nan	0.1000	0.0639
##	8	1.1476	nan	0.1000	0.0565
##	9	1.1113	nan	0.1000	0.0457
##	10	1.0822	nan	0.1000	0.0468
##	20	0.8509	nan	0.1000	0.0280
##	40	0.6255	nan	0.1000	0.0200
##	60	0.4855	nan	0.1000	0.0050
##	80	0.3972	nan	0.1000	0.0097
##	100	0.3239	nan	0.1000	0.0020
##	120	0.2710	nan	0.1000	0.0059
##	140	0.2327	nan	0.1000	0.0035
##	150	0.2125	nan	0.1000	0.0028
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.2362
##	2	1.4603	nan	0.1000	0.1673
##	3	1.3567	nan	0.1000	0.1282
##	4	1.2761	nan	0.1000	0.1166
##	5	1.2033	nan	0.1000	0.0870
##	6	1.1467	nan	0.1000	0.0762
##	7	1.0974	nan	0.1000	0.0626
##	8	1.0569	nan	0.1000	0.0816
##	9	1.0068	nan	0.1000	0.0614
##	10	0.9672	nan	0.1000	0.0558
##	20	0.7006	nan	0.1000	0.0273
##	40	0.4631	nan	0.1000	0.0121
##	60	0.3337	nan	0.1000	0.0059

```

##      80      0.2564      nan      0.1000      0.0041
##     100      0.1995      nan      0.1000      0.0032
##     120      0.1537      nan      0.1000      0.0016
##     140      0.1249      nan      0.1000      0.0013
##     150      0.1125      nan      0.1000      0.0008
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.6094      nan      0.1000      0.1286
##      2      1.5224      nan      0.1000      0.0833
##      3      1.4651      nan      0.1000      0.0714
##      4      1.4188      nan      0.1000      0.0533
##      5      1.3830      nan      0.1000      0.0481
##      6      1.3503      nan      0.1000      0.0414
##      7      1.3238      nan      0.1000      0.0388
##      8      1.2978      nan      0.1000      0.0316
##      9      1.2769      nan      0.1000      0.0400
##     10      1.2507      nan      0.1000      0.0322
##     20      1.0874      nan      0.1000      0.0186
##     40      0.9072      nan      0.1000      0.0098
##     60      0.7977      nan      0.1000      0.0072
##     80      0.7157      nan      0.1000      0.0060
##    100      0.6506      nan      0.1000      0.0051
##    120      0.5975      nan      0.1000      0.0033
##    140      0.5503      nan      0.1000      0.0032
##    150      0.5297      nan      0.1000      0.0024
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.6094      nan      0.1000      0.1936
##      2      1.4853      nan      0.1000      0.1362
##      3      1.3986      nan      0.1000      0.1047
##      4      1.3303      nan      0.1000      0.0872
##      5      1.2744      nan      0.1000      0.0704
##      6      1.2283      nan      0.1000      0.0728
##      7      1.1805      nan      0.1000      0.0588
##      8      1.1422      nan      0.1000      0.0517
##      9      1.1091      nan      0.1000      0.0437
##     10      1.0813      nan      0.1000      0.0542
##     20      0.8660      nan      0.1000      0.0273
##     40      0.6266      nan      0.1000      0.0151
##     60      0.4854      nan      0.1000      0.0063
##     80      0.3922      nan      0.1000      0.0037
##    100      0.3264      nan      0.1000      0.0028
##    120      0.2706      nan      0.1000      0.0046
##    140      0.2309      nan      0.1000      0.0045
##    150      0.2121      nan      0.1000      0.0025
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.6094      nan      0.1000      0.2457
##      2      1.4560      nan      0.1000      0.1669
##      3      1.3527      nan      0.1000      0.1256

```

##	4	1.2720	nan	0.1000	0.0983
##	5	1.2075	nan	0.1000	0.0999
##	6	1.1454	nan	0.1000	0.0800
##	7	1.0934	nan	0.1000	0.0676
##	8	1.0504	nan	0.1000	0.0747
##	9	1.0043	nan	0.1000	0.0657
##	10	0.9636	nan	0.1000	0.0475
##	20	0.6860	nan	0.1000	0.0252
##	40	0.4497	nan	0.1000	0.0147
##	60	0.3260	nan	0.1000	0.0098
##	80	0.2463	nan	0.1000	0.0056
##	100	0.1930	nan	0.1000	0.0033
##	120	0.1540	nan	0.1000	0.0016
##	140	0.1261	nan	0.1000	0.0014
##	150	0.1139	nan	0.1000	0.0013
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1268
##	2	1.5241	nan	0.1000	0.0830
##	3	1.4664	nan	0.1000	0.0662
##	4	1.4222	nan	0.1000	0.0534
##	5	1.3868	nan	0.1000	0.0497
##	6	1.3545	nan	0.1000	0.0401
##	7	1.3271	nan	0.1000	0.0435
##	8	1.3007	nan	0.1000	0.0373
##	9	1.2757	nan	0.1000	0.0302
##	10	1.2562	nan	0.1000	0.0328
##	20	1.0953	nan	0.1000	0.0189
##	40	0.9100	nan	0.1000	0.0094
##	60	0.7993	nan	0.1000	0.0045
##	80	0.7179	nan	0.1000	0.0052
##	100	0.6519	nan	0.1000	0.0033
##	120	0.5980	nan	0.1000	0.0033
##	140	0.5541	nan	0.1000	0.0030
##	150	0.5330	nan	0.1000	0.0019
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1910
##	2	1.4865	nan	0.1000	0.1290
##	3	1.4002	nan	0.1000	0.1052
##	4	1.3310	nan	0.1000	0.0939
##	5	1.2717	nan	0.1000	0.0719
##	6	1.2241	nan	0.1000	0.0715
##	7	1.1793	nan	0.1000	0.0636
##	8	1.1385	nan	0.1000	0.0446
##	9	1.1094	nan	0.1000	0.0536
##	10	1.0762	nan	0.1000	0.0379
##	20	0.8563	nan	0.1000	0.0212
##	40	0.6240	nan	0.1000	0.0100
##	60	0.4882	nan	0.1000	0.0088

##	80	0.3946	nan	0.1000	0.0035
##	100	0.3339	nan	0.1000	0.0035
##	120	0.2793	nan	0.1000	0.0025
##	140	0.2381	nan	0.1000	0.0024
##	150	0.2204	nan	0.1000	0.0024

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.2478
##	2	1.4547	nan	0.1000	0.1568
##	3	1.3538	nan	0.1000	0.1317
##	4	1.2687	nan	0.1000	0.0960
##	5	1.2071	nan	0.1000	0.0877
##	6	1.1504	nan	0.1000	0.0768
##	7	1.1015	nan	0.1000	0.0791
##	8	1.0538	nan	0.1000	0.0881
##	9	1.0005	nan	0.1000	0.0602
##	10	0.9627	nan	0.1000	0.0585
##	20	0.6934	nan	0.1000	0.0219
##	40	0.4552	nan	0.1000	0.0140
##	60	0.3322	nan	0.1000	0.0070
##	80	0.2524	nan	0.1000	0.0043
##	100	0.1974	nan	0.1000	0.0019
##	120	0.1574	nan	0.1000	0.0035
##	140	0.1277	nan	0.1000	0.0026
##	150	0.1146	nan	0.1000	0.0015

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1257
##	2	1.5223	nan	0.1000	0.0827
##	3	1.4649	nan	0.1000	0.0698
##	4	1.4183	nan	0.1000	0.0548
##	5	1.3821	nan	0.1000	0.0435
##	6	1.3529	nan	0.1000	0.0463
##	7	1.3243	nan	0.1000	0.0411
##	8	1.2974	nan	0.1000	0.0367
##	9	1.2741	nan	0.1000	0.0352
##	10	1.2491	nan	0.1000	0.0298
##	20	1.0859	nan	0.1000	0.0189
##	40	0.9054	nan	0.1000	0.0113
##	60	0.7902	nan	0.1000	0.0072
##	80	0.7106	nan	0.1000	0.0039
##	100	0.6455	nan	0.1000	0.0034
##	120	0.5920	nan	0.1000	0.0027
##	140	0.5454	nan	0.1000	0.0017
##	150	0.5251	nan	0.1000	0.0028

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1956
##	2	1.4819	nan	0.1000	0.1316
##	3	1.3960	nan	0.1000	0.1100

##	4	1.3251	nan	0.1000	0.0877
##	5	1.2671	nan	0.1000	0.0754
##	6	1.2192	nan	0.1000	0.0724
##	7	1.1738	nan	0.1000	0.0674
##	8	1.1309	nan	0.1000	0.0587
##	9	1.0941	nan	0.1000	0.0438
##	10	1.0663	nan	0.1000	0.0364
##	20	0.8434	nan	0.1000	0.0272
##	40	0.6160	nan	0.1000	0.0229
##	60	0.4831	nan	0.1000	0.0103
##	80	0.3869	nan	0.1000	0.0136
##	100	0.3167	nan	0.1000	0.0047
##	120	0.2681	nan	0.1000	0.0043
##	140	0.2285	nan	0.1000	0.0043
##	150	0.2101	nan	0.1000	0.0013
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.2455
##	2	1.4529	nan	0.1000	0.1672
##	3	1.3482	nan	0.1000	0.1283
##	4	1.2648	nan	0.1000	0.1065
##	5	1.1967	nan	0.1000	0.0982
##	6	1.1361	nan	0.1000	0.0796
##	7	1.0854	nan	0.1000	0.0640
##	8	1.0444	nan	0.1000	0.0797
##	9	0.9973	nan	0.1000	0.0504
##	10	0.9656	nan	0.1000	0.0645
##	20	0.6857	nan	0.1000	0.0304
##	40	0.4465	nan	0.1000	0.0121
##	60	0.3238	nan	0.1000	0.0099
##	80	0.2483	nan	0.1000	0.0070
##	100	0.1916	nan	0.1000	0.0034
##	120	0.1515	nan	0.1000	0.0026
##	140	0.1228	nan	0.1000	0.0020
##	150	0.1113	nan	0.1000	0.0021
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1259
##	2	1.5227	nan	0.1000	0.0896
##	3	1.4631	nan	0.1000	0.0684
##	4	1.4183	nan	0.1000	0.0542
##	5	1.3832	nan	0.1000	0.0474
##	6	1.3521	nan	0.1000	0.0425
##	7	1.3243	nan	0.1000	0.0405
##	8	1.2980	nan	0.1000	0.0308
##	9	1.2776	nan	0.1000	0.0370
##	10	1.2520	nan	0.1000	0.0322
##	20	1.0878	nan	0.1000	0.0193
##	40	0.9067	nan	0.1000	0.0111
##	60	0.7983	nan	0.1000	0.0070

```

##      80      0.7153      nan      0.1000      0.0038
##     100      0.6496      nan      0.1000      0.0040
##     120      0.5976      nan      0.1000      0.0035
##     140      0.5503      nan      0.1000      0.0025
##     150      0.5288      nan      0.1000      0.0029
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.6094      nan      0.1000      0.1921
##      2      1.4854      nan      0.1000      0.1342
##      3      1.3993      nan      0.1000      0.1052
##      4      1.3304      nan      0.1000      0.0819
##      5      1.2775      nan      0.1000      0.0792
##      6      1.2268      nan      0.1000      0.0670
##      7      1.1833      nan      0.1000      0.0565
##      8      1.1462      nan      0.1000      0.0555
##      9      1.1118      nan      0.1000      0.0537
##     10      1.0788      nan      0.1000      0.0379
##     20      0.8522      nan      0.1000      0.0272
##     40      0.6177      nan      0.1000      0.0096
##     60      0.4829      nan      0.1000      0.0113
##     80      0.3922      nan      0.1000      0.0049
##    100      0.3264      nan      0.1000      0.0030
##    120      0.2767      nan      0.1000      0.0030
##    140      0.2324      nan      0.1000      0.0020
##    150      0.2169      nan      0.1000      0.0013
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.6094      nan      0.1000      0.2384
##      2      1.4552      nan      0.1000      0.1675
##      3      1.3481      nan      0.1000      0.1224
##      4      1.2702      nan      0.1000      0.1031
##      5      1.2051      nan      0.1000      0.0818
##      6      1.1523      nan      0.1000      0.0731
##      7      1.1052      nan      0.1000      0.0924
##      8      1.0496      nan      0.1000      0.0738
##      9      1.0031      nan      0.1000      0.0558
##     10      0.9669      nan      0.1000      0.0591
##     20      0.7078      nan      0.1000      0.0486
##     40      0.4526      nan      0.1000      0.0169
##     60      0.3280      nan      0.1000      0.0062
##     80      0.2451      nan      0.1000      0.0051
##    100      0.1937      nan      0.1000      0.0029
##    120      0.1528      nan      0.1000      0.0036
##    140      0.1219      nan      0.1000      0.0010
##    150      0.1104      nan      0.1000      0.0014
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.6094      nan      0.1000      0.2435
##      2      1.4555      nan      0.1000      0.1621
##      3      1.3515      nan      0.1000      0.1331

```



```
##      4      1.2678      nan      0.1000      0.1048
##      5      1.2021      nan      0.1000      0.0968
##      6      1.1410      nan      0.1000      0.0887
##      7      1.0872      nan      0.1000      0.0785
##      8      1.0385      nan      0.1000      0.0599
##      9      1.0014      nan      0.1000      0.0530
##     10      0.9675      nan      0.1000      0.0468
##     20      0.6883      nan      0.1000      0.0251
##     40      0.4565      nan      0.1000      0.0099
##     60      0.3321      nan      0.1000      0.0041
##     80      0.2558      nan      0.1000      0.0046
##    100      0.2016      nan      0.1000      0.0031
##    120      0.1576      nan      0.1000      0.0038
##    140      0.1264      nan      0.1000      0.0019
##    150      0.1126      nan      0.1000      0.0020
```

```
GBM_Model$finalModel
```

```
## A gradient boosted model with multinomial loss function.
## 150 iterations were performed.
## There were 53 predictors of which 53 had non-zero influence.
```

## ii) The prediction

```
GBM_Prediction <- predict(GBM_Model, newdata=Test_Set)
```

```
GBM_Conf_Matrix <- confusionMatrix(factor(GBM_Prediction),
factor(Test_Set$classe))
```

```
GBM_Conf_Matrix
```

```
## Confusion Matrix and Statistics
```

```
##
```

```
##           Reference
```

```
## Prediction    A    B    C    D    E
```

```
##           A 1672   10    0    0    0
```

```
##           B    1 1119    9    4    1
```

```
##           C    0   10 1014    8    0
```

```
##           D    1    0    3  950    6
```

```
##           E    0    0    0    2 1075
```

```
##
```

```
## Overall Statistics
```

```
##
```

```
##           Accuracy : 0.9907
```

```
##           95% CI : (0.9879, 0.993)
```

```
##           No Information Rate : 0.2845
```

```
##           P-Value [Acc > NIR] : < 2.2e-16
```

```
##
```

```
##           Kappa : 0.9882
```

```
##
```

```
##           McNemar's Test P-Value : NA
```

```
##
```

```
## Statistics by Class:
```

```
##
##               Class: A Class: B Class: C Class: D Class: E
## Sensitivity      0.9988   0.9824   0.9883   0.9855   0.9935
## Specificity      0.9976   0.9968   0.9963   0.9980   0.9996
## Pos Pred Value   0.9941   0.9868   0.9826   0.9896   0.9981
## Neg Pred Value   0.9995   0.9958   0.9975   0.9972   0.9985
## Prevalence       0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate   0.2841   0.1901   0.1723   0.1614   0.1827
## Detection Prevalence 0.2858 0.1927 0.1754 0.1631 0.1830
## Balanced Accuracy 0.9982   0.9896   0.9923   0.9917   0.9966
```

And, as predicted, the accuracy rate of GBM is less than the same of Random Forest model. Here, the out of sample error rate is very little, 0.0084.

#### V. Best Model Selection and its Validation on test\_data

The three models used gave us the following accuracy rates: Decision Tree - 0.4773  
Random Forest - 1 Generalized Boosted Model - 0.9891

So, we choose the model with highest accuracy rate which is Random Forest. And now we will validate and get results of the 20 observations of test\_data via applying Random Forest Model.

```
Predict_Results <- predict(RF_Model, test_data)
Predict_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
```