# Coursera-Pratical-Machine\_learning-Assginment

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### 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. 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).

#### **Data**

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

The data for this project come from this source: http://groupware.les.inf.puc-rio.br/har. If you use the document you create for this class for any purpose please cite them as they have been very generous in allowing their data to be used for this kind of assignment.

```
##Read training and test datasets into R environment
pml_raw <- read.csv("https://d396qusza40orc.cloudfront.net/predmachlearn/pml-
training.csv", header = TRUE)
pml_validation <-
read.csv("https://d396qusza40orc.cloudfront.net/predmachlearn/pml-
testing.csv", header = TRUE)

##Check both Training and testing datasets
dim(pml_raw);dim(pml_validation)

## [1] 19622 160

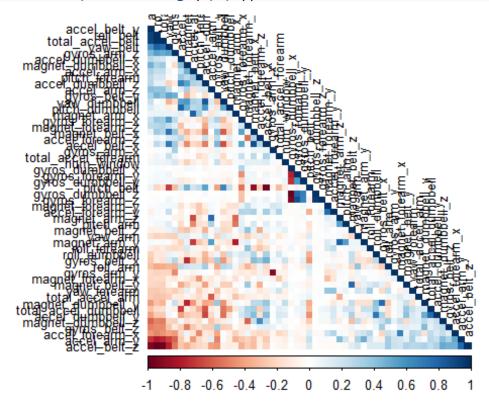
## [1] 20 160</pre>
```

## **Preprocessing data**

```
#Load package for this process
if (!require(caret)) install.packages("caret")
## Loading required package: caret
## Warning: package 'caret' was built under R version 3.5.3
## Loading required package: lattice
## Loading required package: ggplot2
## Warning: package 'ggplot2' was built under R version 3.5.3
library(caret)
if (!require(e1071)) install.packages("e1071")
## Loading required package: e1071
## Warning: package 'e1071' was built under R version 3.5.3
library(e1071)
##split raw data into training and testing datasets
set.seed(123)
split_label <- createDataPartition(y=pml_raw$classe,p=0.7,list = FALSE)</pre>
train<-pml_raw[split_label,]</pre>
test<-pml_raw[-split_label,]</pre>
dim(train); dim(test)
## [1] 13737
               160
## [1] 5885 160
## remove unique data columns
NZV <- nearZeroVar(train, freqCut = 19)</pre>
train <- train[,-NZV]</pre>
test<- test[,-NZV]</pre>
##remove columns with mostly null values
nul_label <- sapply(train, function(x) mean(is.na(x))) >0.95
train<- train[,nul label==FALSE]</pre>
test<- test[,nul_label==FALSE]</pre>
## remove identification variables
train<-train[,-c(1:5)]</pre>
test<-test[,-c(1:5)]
```

### **Data Exploratory Analysis**

```
#Load package for this process
if (!require(corrplot)) install.packages("corrplot")
## Loading required package: corrplot
## Warning: package 'corrplot' was built under R version 3.5.3
## corrplot 0.84 loaded
library(corrplot)
##Check some of columns in the dataset
summary(pml_raw$classe)
## A B C D E
## 5580 3797 3422 3216 3607
##Show correlation between all variables
corrplot(cor(train[,-54]), method = "color", type = "lower", order = "FPC",
tl.cex=0.8, tl.col = rgb(0,0,0))
```

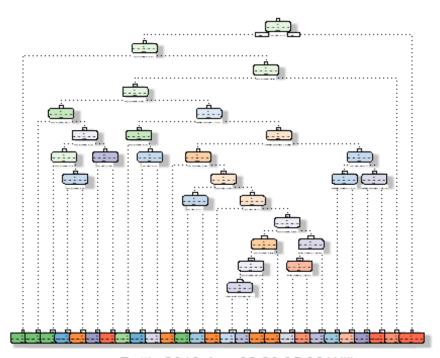


##Model Selection Process

###Decision Tree

```
# Load package for this process
if (!require(rpart)) install.packages("rpart")
```

```
## Loading required package: rpart
if (!require(rpart.plot)) install.packages("rpart.plot")
## Loading required package: rpart.plot
## Warning: package 'rpart.plot' was built under R version 3.5.3
library(rpart.plot); library(rpart)
if (!require(rattle)) install.packages("rattle")
## Loading required package: rattle
## Warning: package 'rattle' was built under R version 3.5.3
## 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(rattle)
## Modeling process
dt_model <- rpart(classe ~ ., data=train, method = 'class')</pre>
fancyRpartPlot(dt_model)
## Warning: labs do not fit even at cex 0.15, there may be some overplotting
```



Rattle 2019-Aug-02 20:05:36 Will

```
dt test predict <- predict(dt model, test, type = "class")</pre>
conf matrix dt test <- confusionMatrix(dt test predict, test$classe)</pre>
conf_matrix_dt_test
## Confusion Matrix and Statistics
##
             Reference
                           C
                                     Ε
## Prediction
                Α
                      В
                                D
                                     7
           A 1496
                           3
##
                    114
                               18
            В
                74
                    843
                          55
                               71
                                    44
##
            C
                0
                     57 830
                               37
                                     3
##
##
            D
                84
                     51 124 778
                                    68
##
            Е
                20
                     74
                          14
                               60 960
##
## Overall Statistics
##
##
                  Accuracy : 0.8338
##
                    95% CI: (0.8241, 0.8432)
##
       No Information Rate: 0.2845
##
       P-Value [Acc > NIR] : < 2.2e-16
##
##
                     Kappa: 0.7901
##
   Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
##
##
                        Class: A Class: B Class: C Class: D Class: E
## Sensitivity
                          0.8937
                                   0.7401
                                            0.8090
                                                     0.8071
                                                              0.8872
## Specificity
                          0.9663
                                   0.9486
                                            0.9800
                                                     0.9336
                                                              0.9650
## Pos Pred Value
                          0.9133
                                   0.7755
                                            0.8954
                                                     0.7041
                                                              0.8511
                                   0.9383
## Neg Pred Value
                          0.9581
                                            0.9605
                                                     0.9611
                                                              0.9744
## Prevalence
                          0.2845
                                   0.1935
                                            0.1743
                                                     0.1638
                                                              0.1839
                                   0.1432
## Detection Rate
                          0.2542
                                                     0.1322
                                                              0.1631
                                            0.1410
## Detection Prevalence
                          0.2783
                                   0.1847
                                            0.1575
                                                     0.1878
                                                              0.1917
                                  0.8444
## Balanced Accuracy
                          0.9300
                                            0.8945
                                                     0.8703
                                                              0.9261
```

#### ###Random Forest

```
if (!require(randomForest)) install.packages("randomForest")
## Loading required package: randomForest
## Warning: package 'randomForest' was built under R version 3.5.3
## 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(randomForest)
set.seed(123)
rf model <- randomForest(classe ~ ., data=train, importance=TRUE)
rf_test_predict <- predict(rf_model, test, type="class")</pre>
conf_matrix_rf_test <- confusionMatrix(rf_test_predict, test$classe)</pre>
conf_matrix_rf_test
## Confusion Matrix and Statistics
##
             Reference
##
## Prediction
                           C
                                 D
                                      Ε
                 Α
            A 1674
##
                      0
                                 0
                 0 1139
##
            В
                            7
                                 0
                                      0
            C
                      0 1019
                                      0
##
                 0
                                 6
##
            D
                 0
                      0
                            0
                              957
                                      0
##
            Е
                 0
                      0
                            0
                                 1 1082
##
## Overall Statistics
##
##
                  Accuracy : 0.9976
                    95% CI: (0.996, 0.9987)
##
##
       No Information Rate: 0.2845
##
       P-Value [Acc > NIR] : < 2.2e-16
##
##
                     Kappa: 0.997
##
   Mcnemar's Test P-Value : NA
##
##
## Statistics by Class:
##
##
                        Class: A Class: B Class: C Class: D Class: E
## Sensitivity
                          1.0000
                                    1.0000
                                             0.9932
                                                      0.9927
                                                                1.0000
                                                      1.0000
## Specificity
                          1.0000
                                    0.9985
                                             0.9988
                                                                0.9998
## Pos Pred Value
                          1.0000
                                    0.9939
                                             0.9941
                                                      1.0000
                                                                0.9991
                                    1.0000
## Neg Pred Value
                                             0.9986
                                                      0.9986
                          1.0000
                                                                1.0000
## Prevalence
                          0.2845
                                    0.1935
                                             0.1743
                                                      0.1638
                                                                0.1839
## Detection Rate
                          0.2845
                                    0.1935
                                             0.1732
                                                      0.1626
                                                                0.1839
## Detection Prevalence
                          0.2845
                                    0.1947
                                             0.1742
                                                      0.1626
                                                                0.1840
                                    0.9993
## Balanced Accuracy
                          1.0000
                                             0.9960
                                                      0.9964
                                                                0.9999
```

###Data Validation The random forest model has been decided using to predict the test data due to the over 99% accuracy and Kappa rate.

```
pml_validation <- pml_validation[,-NZV]
pml_validation<- pml_validation[,nul_label==FALSE]
pml_validation<-pml_validation[,-c(1:5)]

predict(rf_model, pml_validation, type="class")

## 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
## 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</pre>
```