Practical Machine Learning

Prediction Assignment Writeup

1. 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 (see the section on the Weight Lifting Exercise Dataset).

2. Loading and Processing the Raw Data

The data for this project come from this source

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

3. Data downloading

We first set the default working directory and download the require training data and test data accordingly.

```
library(RCurl)

setwd("C:\\Users\\leonardo\\lgomez\\courseradatascience\\8.Practical_Machine_Learning\\Practical_Machine_Learning_Assignment")


if (!file.exists("./data")) {

  dir.create("./data")

}
```

```
            if (!file.exists("./data/pml-training.csv")) {
            url.training <-
"https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
            download.file(url.training, destfile = "./data/pml-training.csv")
            }
            if (!file.exists("./data/pml-testing.csv")) {
            url.testing <-
"https://d396werus45678orc.cloudfront.net/predmachlearn/pml-testing.csv"
            download.file(url.testing, destfile = "./data/pml-testing.csv")
                                                                }
```

4. Reading data and data processing

Continuing with the work, an exploration of the data is made

```
##Data training and test
train<- read.csv("./data/pml-training.csv")
test<- read.csv("./data/pml-testing.csv")
dim(train)
## [1] 19622   160
dim(test)
## [1]  20 160
```

Note that both dataset are having the same variables (160 variables). Next is try remove the near zero variance variables or columns that contain N/A missing values.

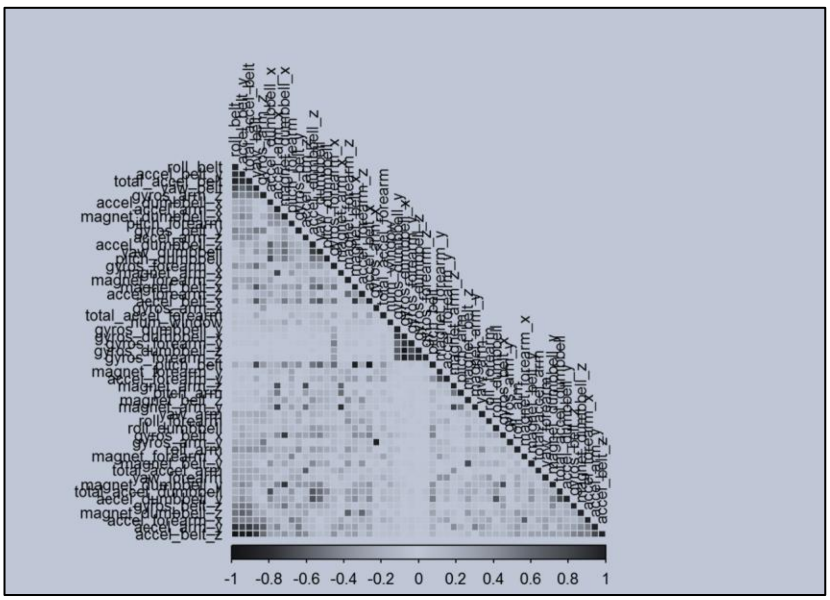
```
train <- train[, colSums(is.na(train)) == 0]
test <- test[, colSums(is.na(test)) == 0]
classe <- train$classe
trainR <- grepl("^X|timestamp|window", names(train))
train <- train[, !trainR]
trainM <- train[, sapply(train, is.numeric)]
trainM$classe <- classe
testR <- grepl("^X|timestamp|window", names(test))
test<- test[, !testR]
testM <- test[, sapply(test, is.numeric)]
```

There were 107 variables with more than 95% of the data missing. Those variables were removed from the data as well. If we built a classification model based on those variables, then we can expect most of the time the variable is missing and therefore we cannot apply the classification rules on them. Therefore, building a model based on variables that's mostly missing is not practical.

Correlation matrix analysis

A correlation among variables is analysed before proceeding to the modeling procedures.

```
corMatrix <- cor(TrainSet[, -54])
corrplot(corMatrix, order = "FPC", method = "color", type = "lower",
         tl.cex = 0.8, tl.col = rgb(0, 0, 0))
```



5. Data Partitioning

Partitioning Training data set into two data sets,70% for train data, 30% for test data as this will be used for cross validation purpose:

```
library(caret)
set.seed(12345)
inTrain <- createDataPartition(trainM$classe, p=0.70, list=F)
train_data <- trainM[inTrain, ]
test_data <- trainM[-inTrain, ]
```

6. Data Prediction and Modelling

Algorithm which will be used for the predictive model here is **Random Forest**

```
setting <- trainControl(method="cv", 5)
RandomForest <- train(classe ~ ., data=train_data, method="rf",
trControl=setting, ntree=250)
RandomForest
```

```
## 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, 10990, 10990, 10989, 10990
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa      Accuracy SD  Kappa SD
##    2    0.9914101  0.9891330  0.001679589  0.002124719
##   27    0.9900270  0.9873842  0.001166909  0.001475135
##   52    0.9862415  0.9825951  0.001442765  0.001824660
##
## Accuracy was used to select the optimal model using  the largest value.
## The final value used for the model was mtry = 2.
```

We estimate the performance of the model build. Getting the accuracy as well as the estimated out-of-sample error.

```
predict_RandomForest <- predict(RandomForest, test_data)
confusionMatrix(test_data$classe, predict_RandomForest)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1672    2    0    0    0
##          B   12 1121    6    0    0
##          C    0   19 1003    4    0
##          D    0    0   27  937    0
##          E    0    0    1    3 1078
##
## Overall Statistics
##
```

```
##                Accuracy : 0.9874
##                  95% CI : (0.9842, 0.9901)
##     No Information Rate : 0.2862
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9841
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9929   0.9816   0.9672   0.9926   1.0000
## Specificity            0.9995   0.9962   0.9953   0.9945   0.9992
## Pos Pred Value         0.9988   0.9842   0.9776   0.9720   0.9963
## Neg Pred Value         0.9972   0.9956   0.9930   0.9986   1.0000
## Prevalence             0.2862   0.1941   0.1762   0.1604   0.1832
## Detection Rate         0.2841   0.1905   0.1704   0.1592   0.1832
## Detection Prevalence   0.2845   0.1935   0.1743   0.1638   0.1839
## Balanced Accuracy      0.9962   0.9889   0.9812   0.9936   0.9996
```

```
accuracy <- postResample(predict_RandomForest, test_data$classe)
error<-1 - as.numeric(confusionMatrix(test_data$classe,
predict_RandomForest)$overall[1])
```

The accuracy of the model is 98.7% and the estimated out-of-sample error is 1.3%

7. Predicting Results on the Test Data

Last we will validate our model building based on the test data provided in the link

```
##  [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
```