Week_4_Prediction_Assignment_Writeup

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Contents


```
#load necessary R packages
library(knitr)
library(dplyr)
library(caret)
library(rpart)
library(rpart.plot)
library(rattle)
library(randomForest)
library(corrplot)
library(e1071)
set.seed(301)
```

1 Introduction

(Velloso, Bulling, Gellersen, Ugulino, & Fuks, 2013)

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]http://groupware.les.inf.puc-rio.br/har (see the section on the Weight Lifting Exercise Dataset).

2 Load Data and cleaning data

The training data for this project are available here:

Training Set

The test data are available here:

Test Set

The next step is loading the dataset from the URL provided above. The training dataset is then partinioned in 2 to create a Training set (70% of the data) for the modeling process and a Test set (with the remaining 30%) for the validations. The testing dataset is not changed and will only be used for the quiz results generation.

```
TrainUrl <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
TestUrl  <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"
TrainFile<-"data/pml-traininig.csv"
TestFile<-"data/pml-testing.csv"
dir.create('data', showWarnings=F)
# download the datasets
if(!file.exists(TrainFile))
{
    download.file(TrainUrl,destfile = TrainFile)
}
training <- read.csv(TrainFile)
if(!file.exists(TestFile))
{
    download.file(TestUrl,destfile = TestFile)
}
testing  <- read.csv(TestFile)

# create a partition using caret with the training dataset on 70,30 ratio
inTrain  <- createDataPartition(training$classe, p=0.7, list=FALSE)

TrainSet <- training[inTrain, ]

TestSet  <- training[-inTrain, ]
dim(TrainSet)
```

```
## [1] 13737   160
```

```
dim(TestSet)
```

```
## [1] 5885  160
```

Both created datasets have 160 variables. Let's clean NA, The Near Zero variance (NZV) variables and the ID variables as well.

```
# remove variables with Nearly Zero Variance
NZV <- nearZeroVar(TrainSet)
TrainSet <- TrainSet[, -NZV]
TestSet  <- TestSet[, -NZV]
dim(TestSet)
```

```
## [1] 5885  105
```

```
dim(TrainSet)
```

```
## [1] 13737   105
```

```
# remove variables that are mostly NA
AllNA    <- sapply(TrainSet, function(x) mean(is.na(x))) > 0.95
TrainSet <- TrainSet[, AllNA==FALSE]
TestSet  <- TestSet[, AllNA==FALSE]
dim(TestSet)
```

```
## [1] 5885   59
```

```
dim(TrainSet)
```

```
## [1] 13737    59
```

```
# remove identification only variables (columns 1 to 5)
TrainSet <- TrainSet[, -(1:5)]
TestSet  <- TestSet[, -(1:5)]
dim(TrainSet)
```

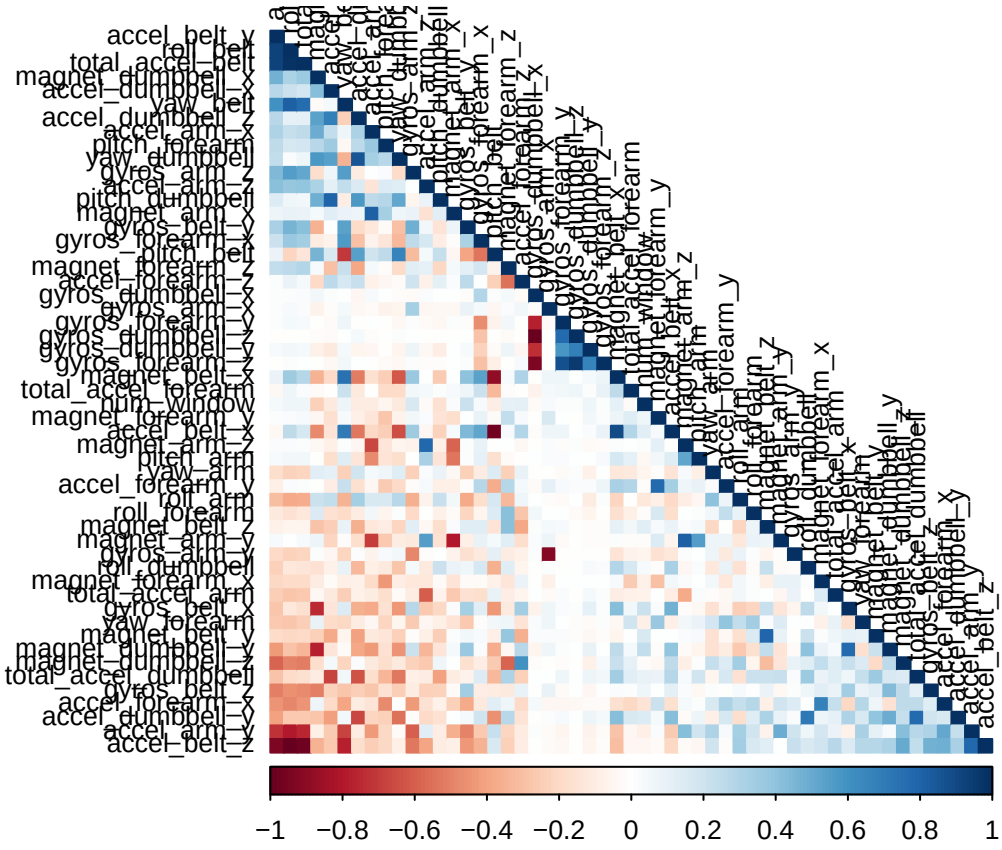
```
## [1] 13737    54
```

After cleaning, we can see that the number of vairables for the analysis are now only 53.

3 Exploratory analysis

A correlation among variables is analysed before proceeing 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))
```



The highly correlated variables are shown in dark colors in the graph above. To make an even more compact analysis, a PCA (Principal Components Analysis) could be performed as pre-processing step to the datasets. Nevertheless, as the correlations are quite few, this step will not be applied for this assignment.

4 Modelling

Three popular methods will be applied to model the regressions (in the Train dataset) and the best one (with higher accuracy when applied to the Test dataset) will be used for the quiz predictions. The methods are: Random Forests, Decision Tree and Generalized Boosted Model, as described below. A Confusion Matrix is plotted at the end of each analysis to better visualize the accuracy of the models.

4.1 Random Forests

```
# model fit
set.seed(301)
controlRF <- trainControl(method="cv", number=3, verboseIter=FALSE)
modFitRandForest <- train(classe ~ ., data=TrainSet, method="rf", trControl=controlRF)
modFitRandForest$finalModel
```

```
##
## Call:
##  randomForest(x = x, y = y, mtry = param$mtry)
```

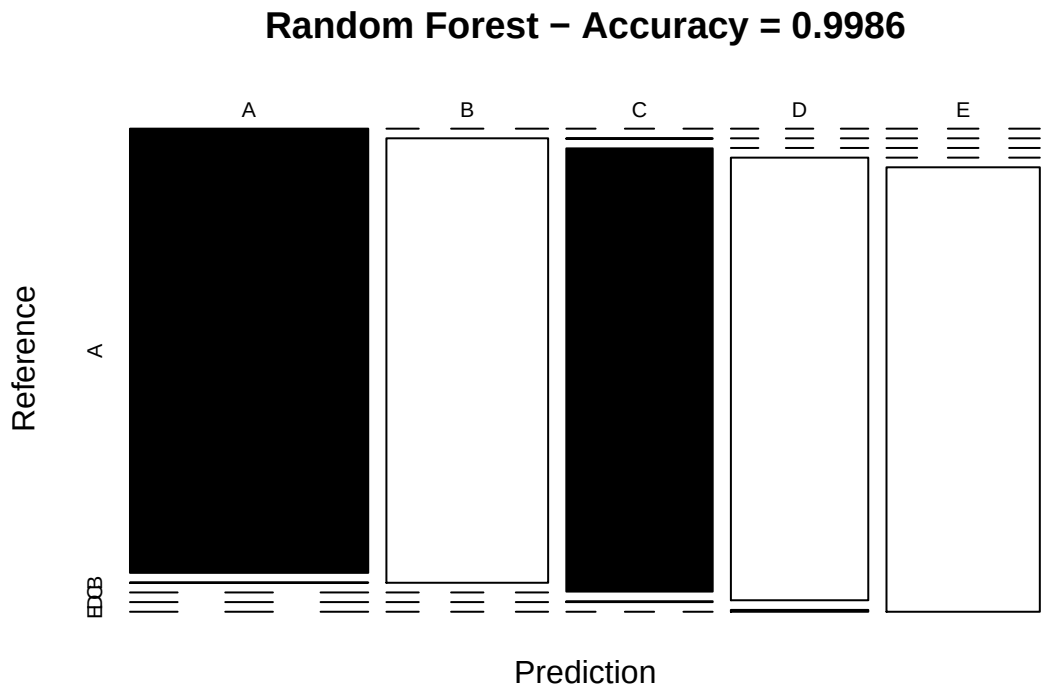
```
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 27
##
##         OOB estimate of  error rate: 0.22%
## Confusion matrix:
##      A    B    C    D    E  class.error
## A 3904    1    0    0    1 0.0005120328
## B    6 2648    3    1    0 0.0037622272
## C    0    4 2392    0    0 0.0016694491
## D    0    0    8 2243    1 0.0039964476
## E    0    1    0    4 2520 0.0019801980
```

```
# prediction on Test dataset
predictRandForest <- predict(modFitRandForest, newdata=TestSet)
confMatRandForest <- confusionMatrix(predictRandForest, TestSet$classe)
confMatRandForest
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1674    1    0    0    0
##          B    0 1137    0    0    0
##          C    0    1 1026    2    0
##          D    0    0    0  962    4
##          E    0    0    0    0 1078
##
## Overall Statistics
##
##                Accuracy : 0.9986
##                  95% CI : (0.9973, 0.9994)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9983
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   0.9982   1.0000   0.9979   0.9963
## Specificity            0.9998   1.0000   0.9994   0.9992   1.0000
## Pos Pred Value         0.9994   1.0000   0.9971   0.9959   1.0000
## Neg Pred Value         1.0000   0.9996   1.0000   0.9996   0.9992
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2845   0.1932   0.1743   0.1635   0.1832
## Detection Prevalence   0.2846   0.1932   0.1749   0.1641   0.1832
## Balanced Accuracy      0.9999   0.9991   0.9997   0.9986   0.9982
```

```
# plot matrix results
plot(confMatRandForest$table, col = confMatRandForest$byClass,
```

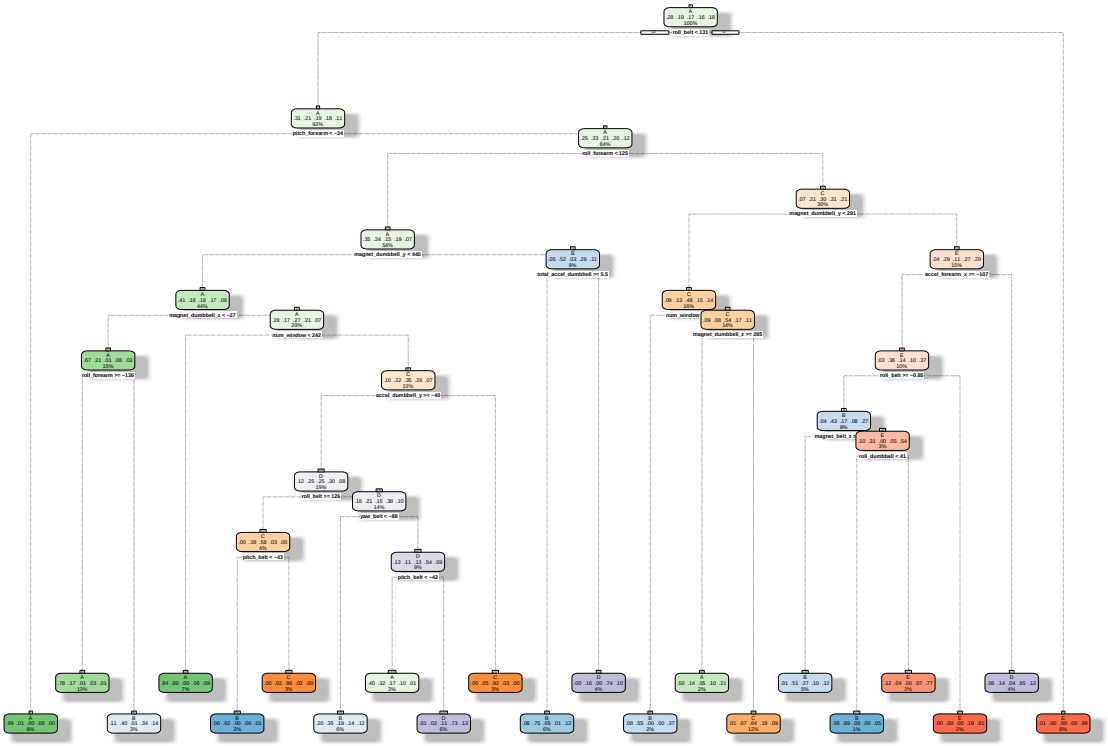
```
    main = paste("Random Forest - Accuracy =",
                 round(confMatRandForest$overall['Accuracy'], 4)))
```



4.2 Decision tree

```
# model fit
set.seed(301)
modFitDecTree <- rpart(classe ~ ., data=TrainSet, method="class")
fancyRpartPlot(modFitDecTree)
```

```
## Warning: labs do not fit even at cex 0.15, there may be some overplotting
```



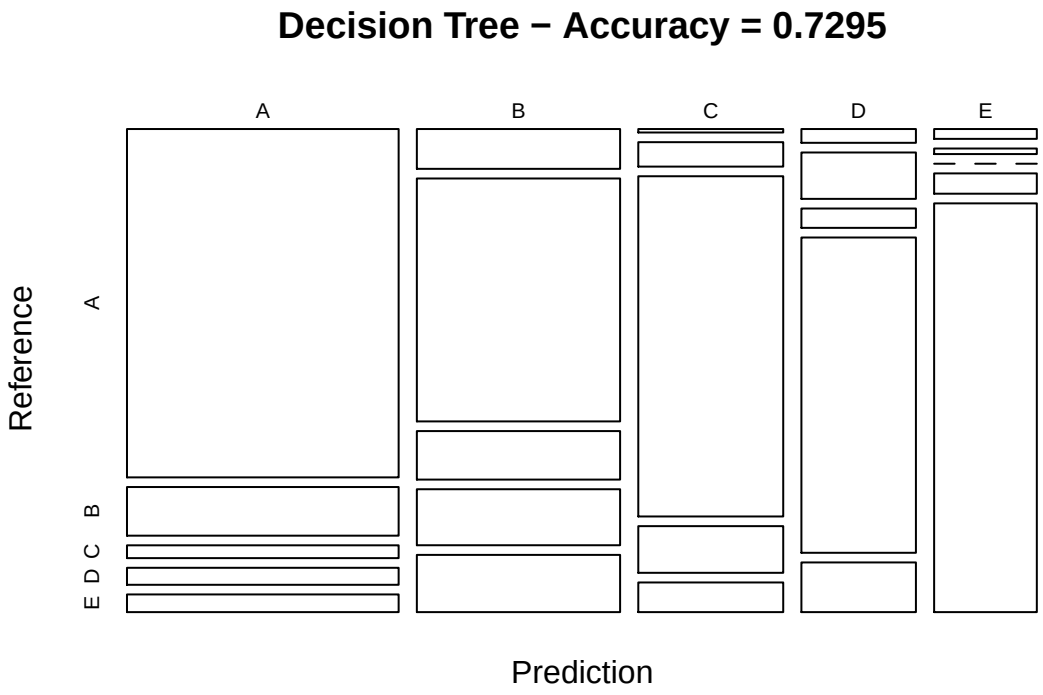
Rattle 2020−Jan−20 17:55:41 User

```
# prediction on Test dataset
predictDecTree <- predict(modFitDecTree, newdata=TestSet, type="class")
confMatDecTree <- confusionMatrix(predictDecTree, TestSet$classe)
confMatDecTree
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1497  209   55   73   76
##          B  128  781  156  180  184
##          C    8   56  780  107   68
##          D   25   84   35  571   90
##          E   16    9    0   33  664
##
## Overall Statistics
##
##                Accuracy : 0.7295
##                  95% CI : (0.7179, 0.7408)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.6556
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
```

```
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.8943   0.6857   0.7602  0.59232   0.6137
## Specificity            0.9019   0.8635   0.9508  0.95245   0.9879
## Pos Pred Value         0.7838   0.5465   0.7655  0.70932   0.9197
## Neg Pred Value         0.9555   0.9197   0.9494  0.92264   0.9190
## Prevalence             0.2845   0.1935   0.1743  0.16381   0.1839
## Detection Rate         0.2544   0.1327   0.1325  0.09703   0.1128
## Detection Prevalence   0.3246   0.2428   0.1732  0.13679   0.1227
## Balanced Accuracy      0.8981   0.7746   0.8555  0.77239   0.8008
```

```r
# plot matrix results
plot(confMatDecTree$table, col = confMatDecTree$byClass,
     main = paste("Decision Tree - Accuracy =",
                  round(confMatDecTree$overall['Accuracy'], 4)))
```



4.3 Generalized Boosted Model (GBM)

```r
# model fit
set.seed(301)
controlGBM <- trainControl(method = "repeatedcv", number = 5, repeats = 1)
modFitGBM  <- train(classe ~ ., data=TrainSet, method = "gbm",
                    trControl = controlGBM, verbose = FALSE)
```

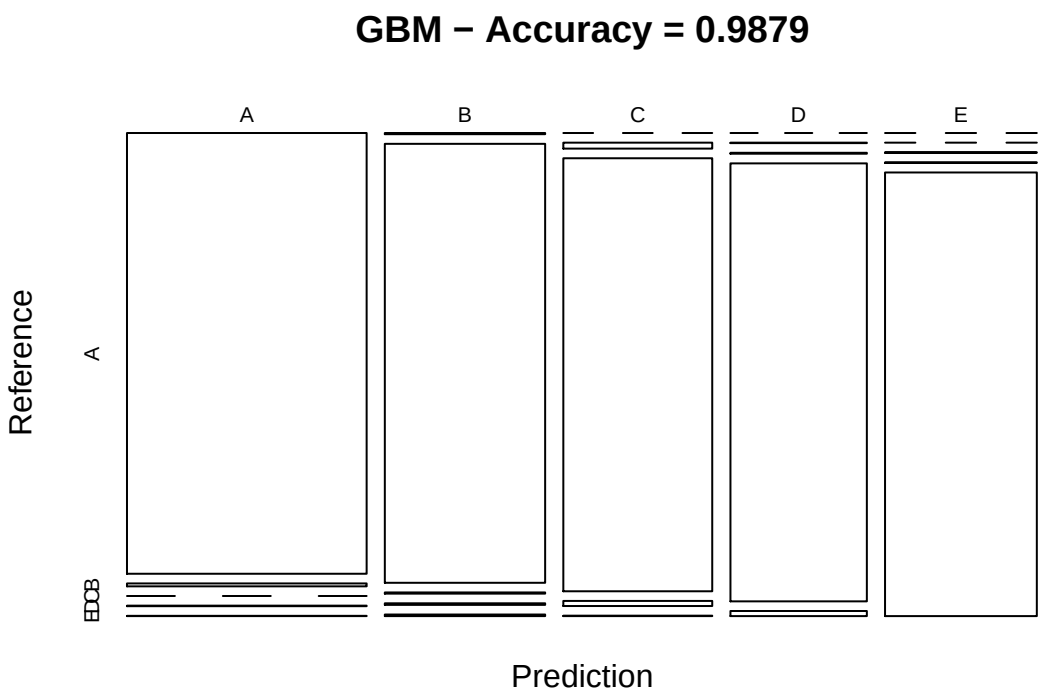
```
modFitGBM$finalModel
```

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

```
# prediction on Test dataset
predictGBM <- predict(modFitGBM, newdata=TestSet)
confMatGBM <- confusionMatrix(predictGBM, TestSet$classe)
confMatGBM
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1671   11    0    2    1
##          B    3 1113    3    4    4
##          C    0   14 1020   12    1
##          D    0    1    2  945   11
##          E    0    0    1    1 1065
##
## Overall Statistics
##
##                Accuracy : 0.9879
##                  95% CI : (0.9848, 0.9906)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9847
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9982   0.9772   0.9942   0.9803   0.9843
## Specificity            0.9967   0.9971   0.9944   0.9972   0.9996
## Pos Pred Value         0.9917   0.9876   0.9742   0.9854   0.9981
## Neg Pred Value         0.9993   0.9945   0.9988   0.9961   0.9965
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2839   0.1891   0.1733   0.1606   0.1810
## Detection Prevalence   0.2863   0.1915   0.1779   0.1630   0.1813
## Balanced Accuracy      0.9974   0.9871   0.9943   0.9887   0.9919
```

```
# plot matrix results
plot(confMatGBM$table, col = confMatGBM$byClass,
     main = paste("GBM - Accuracy =", round(confMatGBM$overall['Accuracy'], 4)))
```



5 Applying the selected Model to the Test Data

The accuracy of the 3 regression modeling methods above are:

- Random Forest : 0.9968
- Decision Tree : 0.8291
- GBM : 0.9884 In that case, the Random Forest model will be applied to predict the 20 quiz results (testing dataset) as shown below.

```
predictTEST <- predict(modFitRandForest, newdata=testing)
predictTEST
```

```
##  [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
```

6 References

[]

Velloso, E., Bulling, A., Gellersen, H., Ugulino, W., & Fuks, H. (2013). Qualitative activity recognition of weight lifting exercises. *ACM Int. Conf. Proceeding Ser.*, 116–123. doi:10.1145/2459236.2459256