Peer-graded Assignment: Prediction Assignment Writeup

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Summary

This is the final report of the Peer Assessment project from the Practical Machine Learning, John's Hopkins University Data Science Specialization course. It was written and coded in RStudio, using its knitr functions and published in the html and markdown format. The goal of this project is to predict the manner in which the six participants performed the exercises. The machine learning algorithm, which uses the classes variable in the training set, is applied to the 20 test cases available in the test data.

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 types 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 dumbbell 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.

Data Source

The training and test data for this project are collected using the link below:

https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv

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.

The full reference of this data is as follows:

Velloso, E.; Bulling, A.; Gellersen, H.; Ugulino, W.; Fuks, H. **"Qualitative Activity Recognition of Weight Lifting Exercises. Proceedings of 4th International Conference in Cooperation with SIGCHI (Augmented Human '13)"**. Stuttgart, Germany: ACM SIGCHI, 2013.

Loading and Cleaning of Data

Set working directory.

```
Setwd("~/Documents/RProgramming Reference/courses-master/08_PracticalMachineLearning/027forecasting")
```

Load required R packages and set a seed.

```
library(lattice)
library(ggplot2)
library(caret)
library(rpart)
library(rpart.plot)
library(corrplot)
library(rattle)
library(randomForest)
library(RColorBrewer)

set.seed(222)
```

Load data for training and test datasets.

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

data_train <- read.csv(url(url_train), strip.white = TRUE, na.strings = c("NA",""))
data_quiz  <- read.csv(url(url_quiz),  strip.white = TRUE, na.strings = c("NA",""))

dim(data_train)
```

```
[1] 19622   160
```

```
dim(data_quiz)
```

```
[1]  20 160
```

Create two partitions (75% and 25%) within the original training dataset.

```
in_train  <- createDataPartition(data_train$classe, p=0.75, list=FALSE)
train_set <- data_train[ in_train, ]
test_set  <- data_train[-in_train, ]

dim(train_set)
```

```
[1] 14718   160
```

```
dim(test_set)
```

```
[1] 4904  160
```

The two datasets (train_set and test_set) have a large number of NA values as well as near-zero-variance (NZV) variables. Both will be removed together with their ID variables.

```
nzv_var <- nearZeroVar(train_set)

train_set <- train_set[ , -nzv_var]
test_set  <- test_set [ , -nzv_var]

dim(train_set)
```

```
[1] 14718   120
```

```
dim(test_set)
```

```
[1] 4904  120
```

Remove variables that are mostly NA. A threshlod of 95 % is selected.

```
na_var <- sapply(train_set, function(x) mean(is.na(x))) > 0.95
train_set <- train_set[ , na_var == FALSE]
test_set  <- test_set [ , na_var == FALSE]

dim(train_set)
```

```
[1] 14718    59
```

```
dim(test_set)
```

```
[1] 4904   59
```

Since columns 1 to 5 are identification variables only, they will be removed as well.

```
train_set <- train_set[ , -(1:5)]
test_set  <- test_set [ , -(1:5)]

dim(train_set)
```

```
[1] 14718    54
```

```
dim(test_set)
```

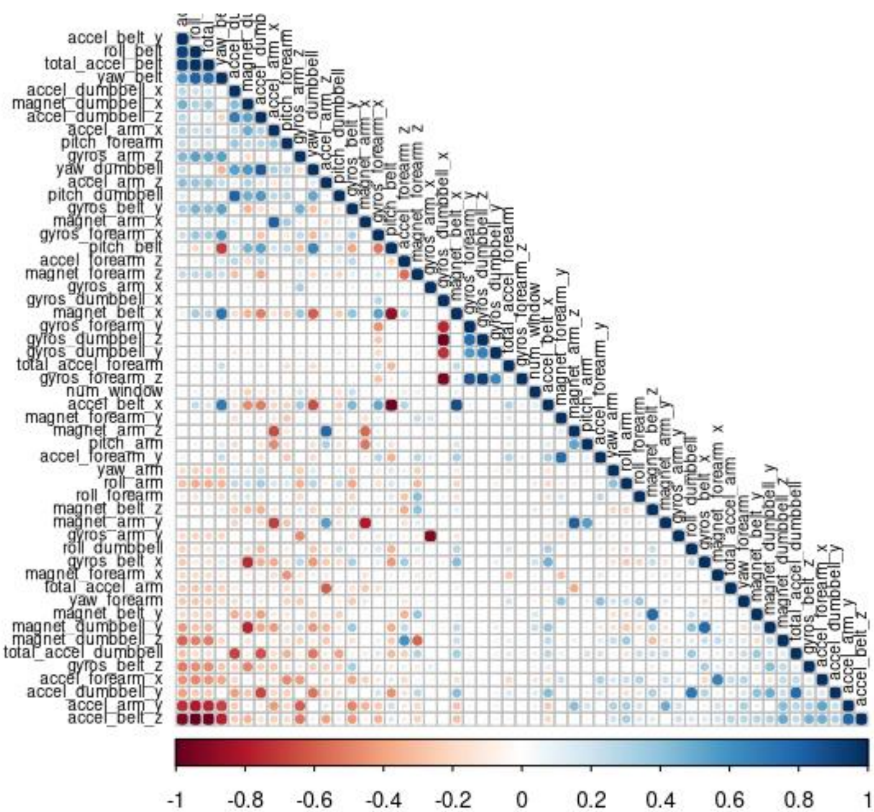
```
[1] 4904   54
```

The number of variables for the analysis has been reduced from the original 160 down to 54.

Correlation Analysis

Correlation analysis between the variables before the modeling work itself is done. The “FPC” is used as the first principal component order.

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



If two variables are highly correlated their colors are either dark blue (for a positive correlation) or dark red (for a negative correlations). Because there are only few strong correlations among the input variables, the Principal Components Analysis (PCA) will not be performed in this analysis. Instead, a few different prediction models will be built to have a better accuracy.

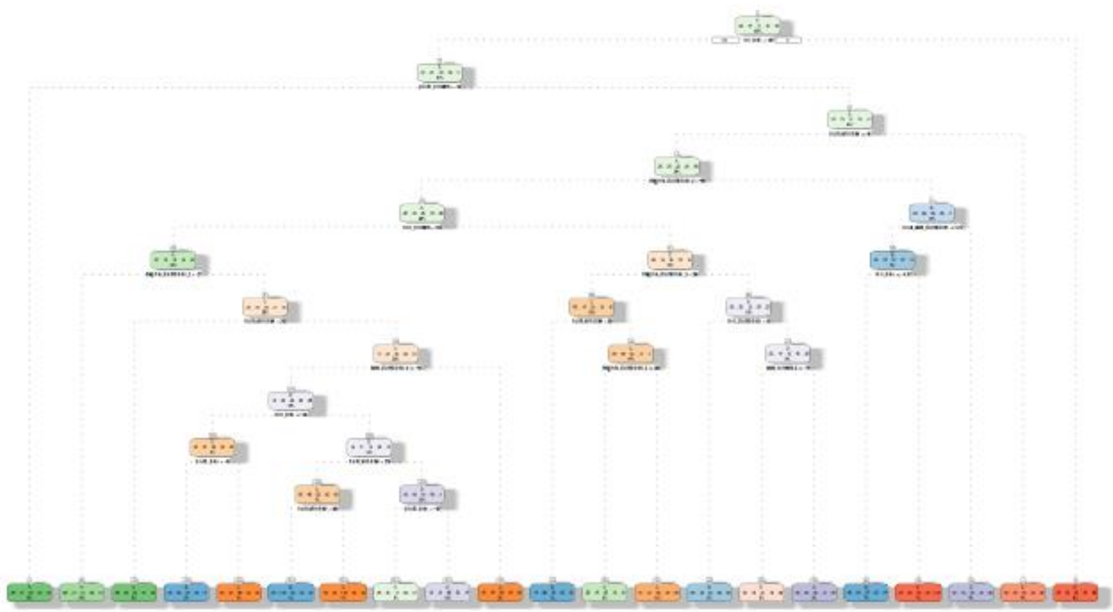
Prediction Models

Decision Tree Model

```
set.seed(2222)

fit_decision_tree <- rpart(classe ~ ., data = train_set, method="class")

fancyRpartPlot(fit_decision_tree)
```



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Predictions of the decision tree model on test_set.

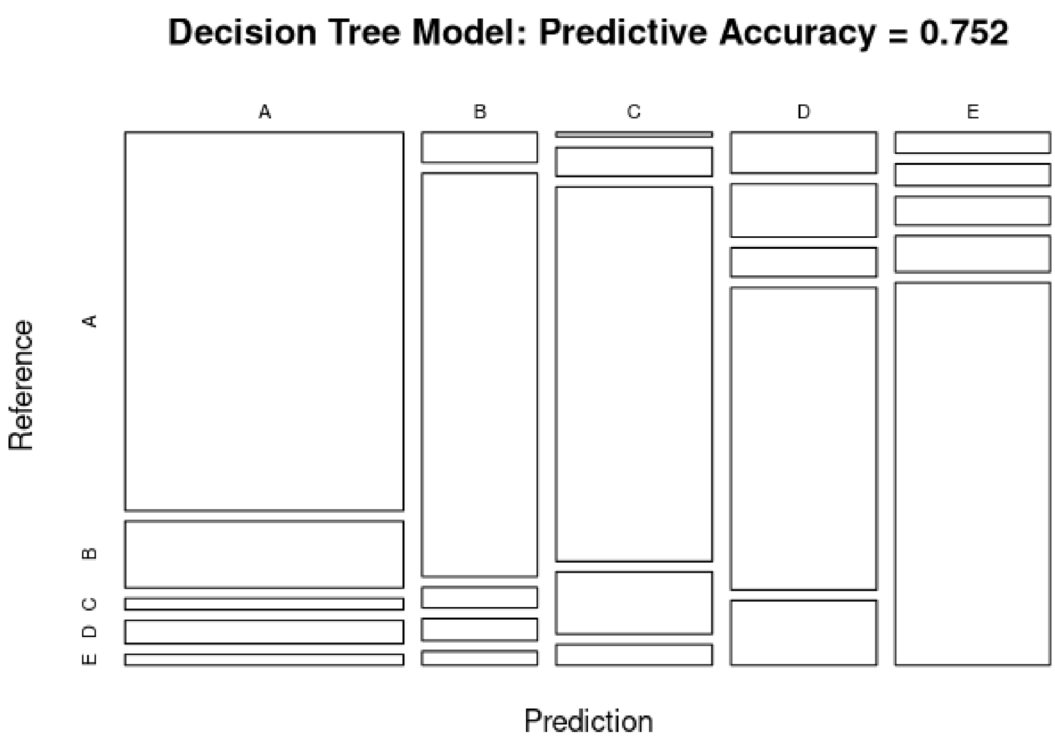
```
predict_decision_tree <- predict(fit_decision_tree, newdata = test_set, type=
"class")

conf_matrix_decision_tree <- confusionMatrix(predict_decision_tree, factor(te
st_set$classe))

conf_matrix_decision_tree
```

```
Confusion Matrix and Statistics

          Reference
Prediction    A    B    C    D    E
         A 1238  218   37   76   36
         B   41  547   28   30   19
         C    8   53  688  114   38
         D   70   91   50  518  111
         E   38   40   52   66  697

Overall Statistics

               Accuracy : 0.752
                 95% CI : (0.7397, 0.7641)
    No Information Rate : 0.2845
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.685

 Mcnemar's Test P-Value : < 2.2e-16

Statistics by Class:

                     Class: A Class: B Class: C Class: D Class: E
Sensitivity            0.8875   0.5764   0.8047   0.6443   0.7736
Specificity            0.8954   0.9702   0.9474   0.9215   0.9510
Pos Pred Value         0.7713   0.8226   0.7636   0.6167   0.7805
Neg Pred Value         0.9524   0.9052   0.9583   0.9296   0.9491
Prevalence             0.2845   0.1935   0.1743   0.1639   0.1837
Detection Rate         0.2524   0.1115   0.1403   0.1056   0.1421
Detection Prevalence   0.3273   0.1356   0.1837   0.1713   0.1821
Balanced Accuracy      0.8914   0.7733   0.8760   0.7829   0.8623
```

The predictive accuracy of the decision tree model is relatively low at 75.2 %.

Plot the predictive accuracy of the decision tree model.

```
plot(conf_matrix_decision_tree$table, col = conf_matrix_decision_tree$byClass
,
     main = paste("Decision Tree Model: Predictive Accuracy =",
                  round(conf_matrix_decision_tree$overall['Accuracy'], 4)))
```



Generalized Boosted Model (GBM)

```
set.seed(2222)
ctrl_GBM <- trainControl(method = "repeatedcv", number = 5, repeats = 2)
fit_GBM  <- train(classe ~ ., data = train_set, method = "gbm",
                  trControl = ctrl_GBM, verbose = FALSE)
fit_GBM$finalModel
```

```
A gradient boosted model with multinomial loss function.
150 iterations were performed.
There were 53 predictors of which 52 had non-zero influence.
```

Predictions of the GBM on test_set.

```
predict_GBM <- predict(fit_GBM, newdata = test_set)
conf_matrix_GBM <- confusionMatrix(predict_GBM, factor(test_set$classe))
conf_matrix_GBM
```

```
Confusion Matrix and Statistics

          Reference
Prediction    A    B    C    D    E
         A 1392    6    0    1    0
         B    3  927    4    3    3
         C    0   12  842   12    2
         D    0    4    9  786    9
         E    0    0    0    2  887

Overall Statistics

               Accuracy : 0.9857
                 95% CI : (0.982, 0.9889)
    No Information Rate : 0.2845
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.9819

 Mcnemar's Test P-Value : NA
```

```
Statistics by Class:

                     Class: A Class: B Class: C Class: D Class: E
Sensitivity            0.9978   0.9768   0.9848   0.9776   0.9845
Specificity            0.9980   0.9967   0.9936   0.9946   0.9995
Pos Pred Value         0.9950   0.9862   0.9700   0.9728   0.9978
Neg Pred Value         0.9991   0.9945   0.9968   0.9956   0.9965
Prevalence             0.2845   0.1935   0.1743   0.1639   0.1837
Detection Rate         0.2838   0.1890   0.1717   0.1603   0.1809
Detection Prevalence   0.2853   0.1917   0.1770   0.1648   0.1813
Balanced Accuracy      0.9979   0.9868   0.9892   0.9861   0.9920
```

The predictive accuracy of the GBM is relatively high at 98.57 %.

Random Forest Model

```r
set.seed(2222)
ctrl_RF <- trainControl(method = "repeatedcv", number = 5, repeats = 2)
fit_RF  <- train(classe ~ ., data = train_set, method = "rf",
                  trControl = ctrl_RF, verbose = FALSE)
fit_RF$finalModel
```

```
Call:
 randomForest(x = x, y = y, mtry = param$mtry, verbose = FALSE)
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 27

        OOB estimate of  error rate: 0.24%
Confusion matrix:
     A    B    C    D    E  class.error
A 4183    1    0    0    1 0.0004778973
B    8 2836    3    1    0 0.0042134831
```

```
C    0    6 2561    0    0 0.0023373588
D    0    0    7 2404    1 0.0033167496
E    0    1    0    7 2698 0.0029563932
```

Predictions of the random forest model on test_set.

```
predict_RF <- predict(fit_RF, newdata = test_set)
conf_matrix_RF <- confusionMatrix(predict_RF, factor(test_set$classe))
conf_matrix_RF
```

```
Confusion Matrix and Statistics

          Reference
Prediction    A    B    C    D    E
         A 1395    3    0    0    0
         B    0  946    2    0    0
         C    0    0  853    6    0
         D    0    0    0  798    1
         E    0    0    0    0  900

Overall Statistics

               Accuracy : 0.9976
                 95% CI : (0.9957, 0.9987)
    No Information Rate : 0.2845
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.9969

 Mcnemar's Test P-Value : NA
```

```
Statistics by Class:

                     Class: A Class: B Class: C Class: D Class: E
Sensitivity            1.0000   0.9968   0.9977   0.9925   0.9989
Specificity            0.9991   0.9995   0.9985   0.9998   1.0000
Pos Pred Value         0.9979   0.9979   0.9930   0.9987   1.0000
Neg Pred Value         1.0000   0.9992   0.9995   0.9985   0.9998
Prevalence             0.2845   0.1935   0.1743   0.1639   0.1837
Detection Rate         0.2845   0.1929   0.1739   0.1627   0.1835
Detection Prevalence   0.2851   0.1933   0.1752   0.1629   0.1835
Balanced Accuracy      0.9996   0.9982   0.9981   0.9961   0.9994
```

The predictive accuracy of the Random Forest model is excellent at 99.8 %.

Applying the Best Predictive Model to the Test Data

The following are the predictive accuracy of the three models:

- Decision Tree Model: 75.20 %
- Generalized Boosted Model: 98.57 %
- Random Forest Model: 99.80 %

The Random Forest model is selected and applied to make predictions on the 20 data points from the original testing dataset (data_quiz).

```
predict_quiz <- as.data.frame(predict(fit_RF, newdata = data_quiz))
predict_quiz
```

```
predict(fit_RF, newdata = data_quiz)
1                                      B
2                                      A
3                                      B
4                                      A
5                                      A
6                                      E
```

7	D
8	B
9	A
10	A
11	B
12	C
13	B
14	A
15	E
16	E
17	A
18	B
19	B
20	B

This is the conclusion.