Practical Machine Learning Project Report

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Target Summary

In this project is 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

Note: The data for this project come from this source: http://groupware.les.inf.puc-rio.br/har.

Libraries used in this project

```r
library(caret)
```

```
## Loading required package: lattice
```

```
## Loading required package: ggplot2
```

```r
library(rpart)
library(rpart.plot)
library(RColorBrewer)
library(rattle)
```

```
## Rattle: A free graphical interface for data science with R.
## Version 5.1.0 Copyright (c) 2006-2017 Togaware Pty Ltd.
## Type 'rattle()' to shake, rattle, and roll your data.
```

```r
library(randomForest)
```

```
## 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
```

Loading data sets

```r
setwd("C:/Users/use/Documents/cat")

training <- read.csv("pml-training.csv",na.strings=c("NA","#DIV/0!", ""))
```

{r, echo=FALSE} dim (training) "'

```r
testing <- read.csv("pml-testing.csv",na.strings=c("NA","#DIV/0!", ""))
```

{r, echo=FALSE} dim (testing)

```
#The training set consists of 19622 observations of 160 variables
#The testing set consists of 20 observations of 160 variables
```

-The training set consists of 19622 observations of 160 variables

-The testing set consists of 20 observations of 160 variables

Cleaning data

Columns in the orignal training and testing datasets that are mostly filled with missing values are then removed count the number of missing values in each column of the full training dataset

```r
training <-training[,colSums(is.na(training)) == 0]
testing <-testing[,colSums(is.na(testing)) == 0]
```

```r
training   <-training[,-c(1:7)]
testing <-testing[,-c(1:7)]

dim ( training )
```

```
## [1] 19622    53
```

```r
dim ( testing  )
```

```
## [1] 20 53
```

zero variance predictors

Diagnoses predictors that have one unique value (i.e. are zero variance predictors) or predictors that are have both of the following characteristics

```r
ColumnsZVar <- nearZeroVar(training, saveMetrics = TRUE)
training <- training[, ColumnsZVar$nzv==FALSE]
training$classe = factor(training$classe)
```

Partitioning the training data This validation dataset will allow us to perform cross validation when developing our model.

Partitioning the training data set to allow cross-validation

```r
set.seed(1234)
subTrain <- createDataPartition(y=training$classe, p=.75, list=FALSE)
```

```r
TheTraining <- training[subTrain, ]
TheTesting <- training[-subTrain, ]
```

Ddataset contains 59 variables, with the last column containing the 'class' variable we are trying to predict.

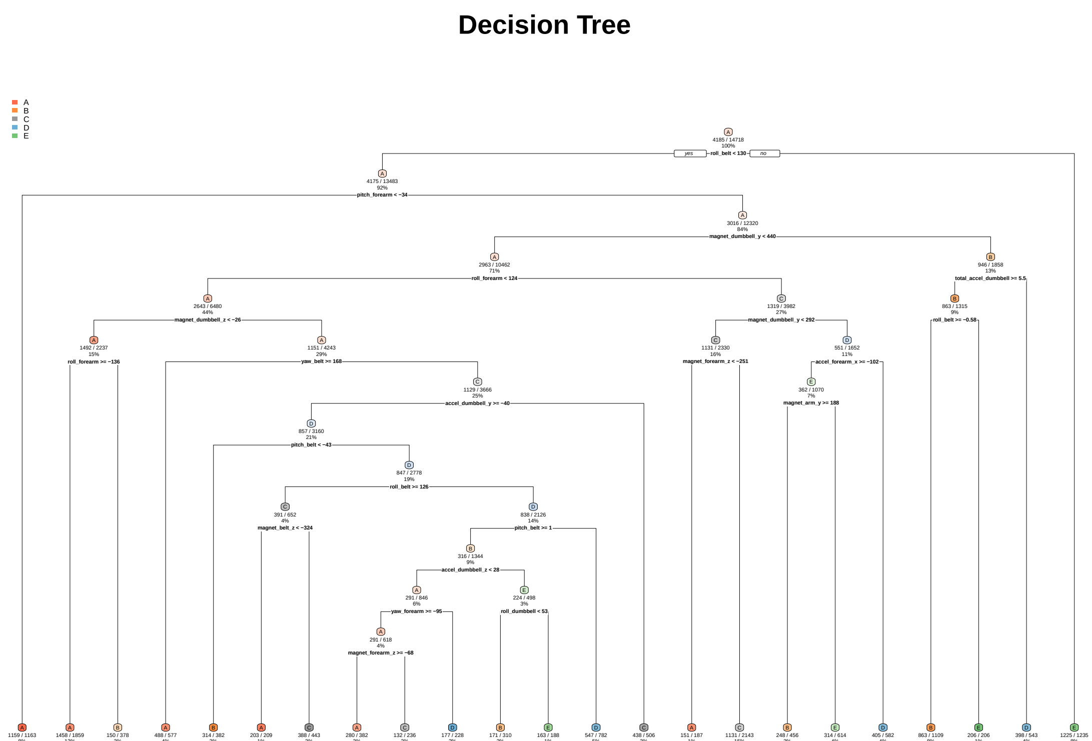
Modelprediction 1 : Using Decision Tree

```r
modelDT <- rpart(classe ~ ., data=TheTraining, method="class")
```

```r
predictionDT <- predict(modelDT, TheTesting, type ="class")
```

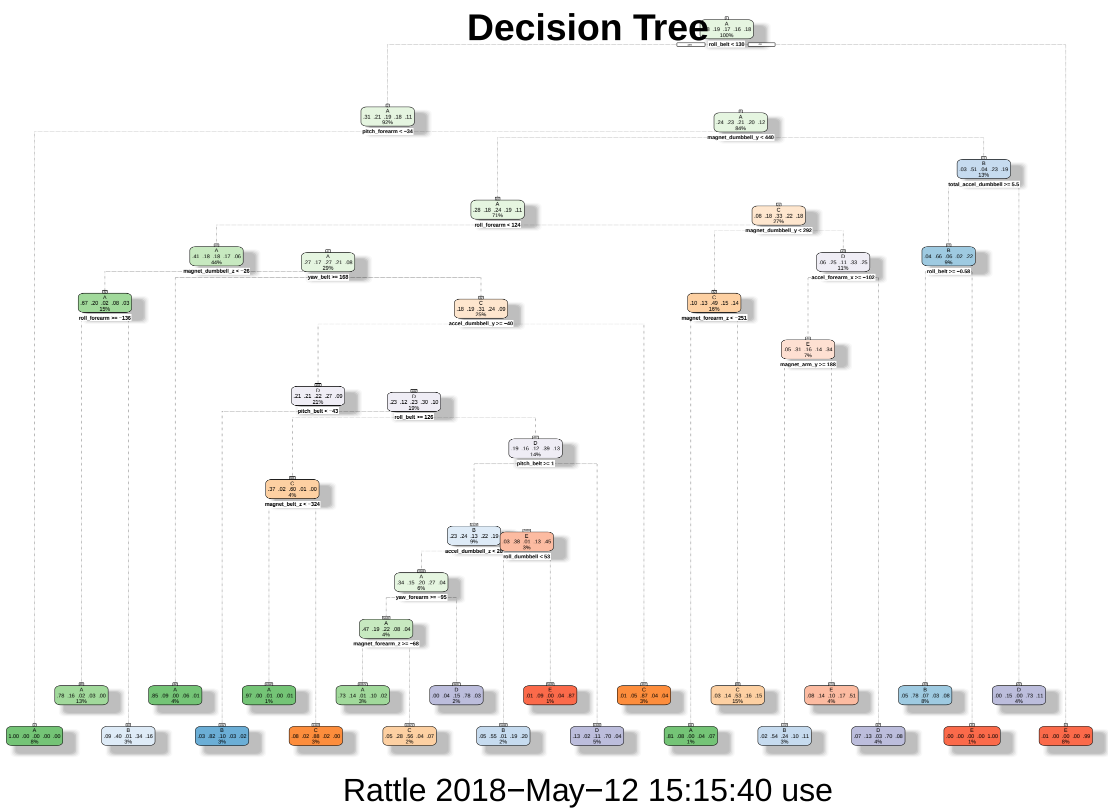
Plot of the Decision Tree

```r
rpart.plot(modelDT, main="Decision Tree ", extra=102, under=TRUE, faclen=0)
```




```r
fancyRpartPlot (modelDT, main="Decision Tree")
```

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



Test results on our subTesting data set:

```r
confusionMatrix(predictionDT,TheTesting$classe)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1235  157   16   50   20
##          B   55  568   73   80  102
##          C   44  125  690  118  116
##          D   41   64   50  508   38
##          E   20   35   26   48  625
##
## Overall Statistics
##
##                Accuracy : 0.7394
##                  95% CI : (0.7269, 0.7516)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.6697
##  Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
```

```
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.8853   0.5985   0.8070   0.6318   0.6937
## Specificity            0.9307   0.9216   0.9005   0.9529   0.9678
## Pos Pred Value         0.8356   0.6469   0.6313   0.7247   0.8289
## Neg Pred Value         0.9533   0.9054   0.9567   0.9296   0.9335
## Prevalence             0.2845   0.1935   0.1743   0.1639   0.1837
## Detection Rate         0.2518   0.1158   0.1407   0.1036   0.1274
## Detection Prevalence   0.3014   0.1790   0.2229   0.1429   0.1538
## Balanced Accuracy      0.9080   0.7601   0.8537   0.7924   0.8307
```

The Confusion Matrix achieved 0.7394 % accuracy. Here, the 95% CI : (0.7269, 0.7516). The Kappa statistic of 0.6697 reflects the out-of-sample error. For the above values is necessary to use the method toRandom Forest Model determineis much better estimator and predictor.

Applied the Random Forest Model and it has shown significant amount of accuracy in prediction.

Modelprediction 2 : Using Random Forest

```
modelRF <- randomForest(classe ~. , data=TheTraining, method="class")
print (modelRF)
```

```
##
## Call:
##  randomForest(formula = classe ~ ., data = TheTraining, method = "class")
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 7
##
##         OOB estimate of  error rate: 0.46%
## Confusion matrix:
##      A    B    C    D    E  class.error
## A 4182    3    0    0    0 0.0007168459
## B   13 2831    4    0    0 0.0059691011
## C    0   14 2550    3    0 0.0066225166
## D    0    0   19 2390    3 0.0091210614
## E    0    1    2    5 2698 0.0029563932
```

Predicting:

```
predictionRF <- predict(modelRF, TheTesting, type = "class")
```

Test results on subTesting data set:

```
confusionMatrix(predictionRF, TheTesting$classe)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1395    3    0    0    0
##          B    0  943   10    0    0
```

```
##          C    0    3  844    5    0
##          D    0    0    1  799    0
##          E    0    0    0    0  901
##
## Overall Statistics
##
##                Accuracy : 0.9955
##                  95% CI : (0.9932, 0.9972)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9943
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   0.9937   0.9871   0.9938   1.0000
## Specificity            0.9991   0.9975   0.9980   0.9998   1.0000
## Pos Pred Value         0.9979   0.9895   0.9906   0.9988   1.0000
## Neg Pred Value         1.0000   0.9985   0.9973   0.9988   1.0000
## Prevalence             0.2845   0.1935   0.1743   0.1639   0.1837
## Detection Rate         0.2845   0.1923   0.1721   0.1629   0.1837
## Detection Prevalence   0.2851   0.1943   0.1737   0.1631   0.1837
## Balanced Accuracy      0.9996   0.9956   0.9926   0.9968   1.0000
```

The Confusion Matrix achieved 99.51% accuracy.in the 95% CI : (0.9927, 0.9969) and the OOB (Out-Of-Bag) Error Rate is 0.43%.The Kappa statistic of 0.9938 reflects the out-of-sample error

Decision

As expected, Random Forest algorithm performed better than Decision Trees. Accuracy for Random Forest model was Accuracy : 0.9951 and (95% CI: ((0.9927, 0.9969))) compared to 95% CI : (0.7269, 0.7516) for Decision Tree model. The random Forest model is choosen. The accuracy of the model is 0.995. The expected out-of-sample error is estimated at 0.005, or 0.5%. The expected out-of-sample error is calculated as 1 - accuracy for predictions made against the cross-validation set. Our Test data set comprises 20 cases. With an accuracy above 99% on our cross-validation data, we can expect that very few, or none, of the test samples will be missclassified.

Conclusion

Of the two Prediction Methods used in the study, accuracy was better for the The Random Forest method since the Confusion Matrix achieves approximately only. The random forest clearly performs better, approaching 99% accuracy for in-sample and out-of-sample error so we will select this model and apply it to the test data set. We use the provided function to classify 20 data points from the test set by the type of lift. We then upload these classifications to Coursera to confirm that the model is working correctly.

Submission

```r
answers<- as.vector(predictionRF[1:20])
pml_write_files  =  function ( x ) {
  n  =  length ( x )
```

```r
  for ( i  in  1 : n ) {
    filename  =  paste0 ( "problem_id_" , i , ".txt" )
    write.table ( x [ i ] , file = filename , quote = FALSE , row.names = FALSE , col.names = FALSE )
  }
}

pml_write_files ( answers )
```