R Notebook

Pull Data

```r
library(caret)
```

```
## Warning: package 'caret' was built under R version 3.4.3
## Loading required package: lattice
## Loading required package: ggplot2
```

```r
library(rpart)
library(randomForest)
```

```
## Warning: package 'randomForest' was built under R version 3.4.3
## randomForest 4.6-12
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
## The following object is masked from 'package:ggplot2':
##
##     margin
```

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

```
## Warning: package 'rpart.plot' was built under R version 3.4.3
```

```r
library(rattle)
```

```
## Warning: package 'rattle' was built under R version 3.4.3
## 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.
##
## Attaching package: 'rattle'
## The following object is masked from 'package:randomForest':
##
##     importance
```

We begin by pulling the data from the excel files

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

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

Splitting the training data

We now split the training data into a training group (70%) and a testing group (30%).

```
set.seed(2121)

train <- createDataPartition(y=pml_training$classe, p=0.7, list=FALSE)

in_train <- pml_training[train,]

in_test <- pml_training[-train,]
```

Cleaning the data

In order to create a viable prediction model, we need to cut out the useless variables.

The first seven variables are of no use to us and should be removed.

```
in_train <- in_train[, -c(1:7)]
in_test <- in_test[, -c(1:7)]

dim(in_train)
```

```
## [1] 13737   153
```

```
dim(in_test)
```

```
## [1] 5885  153
```

Next, we delete columns that have scarce data. We want columns of which at least 10% of their values are not "NA".

```
in_train <- in_train[, colSums(is.na(in_train))==0]
in_test <- in_test[, colSums(is.na(in_test))==0]

dim(in_train)
```

```
## [1] 13737    53
```

```
dim(in_test)
```

```
## [1] 5885   53
```

We now have the data sets cut down to 53 variables.

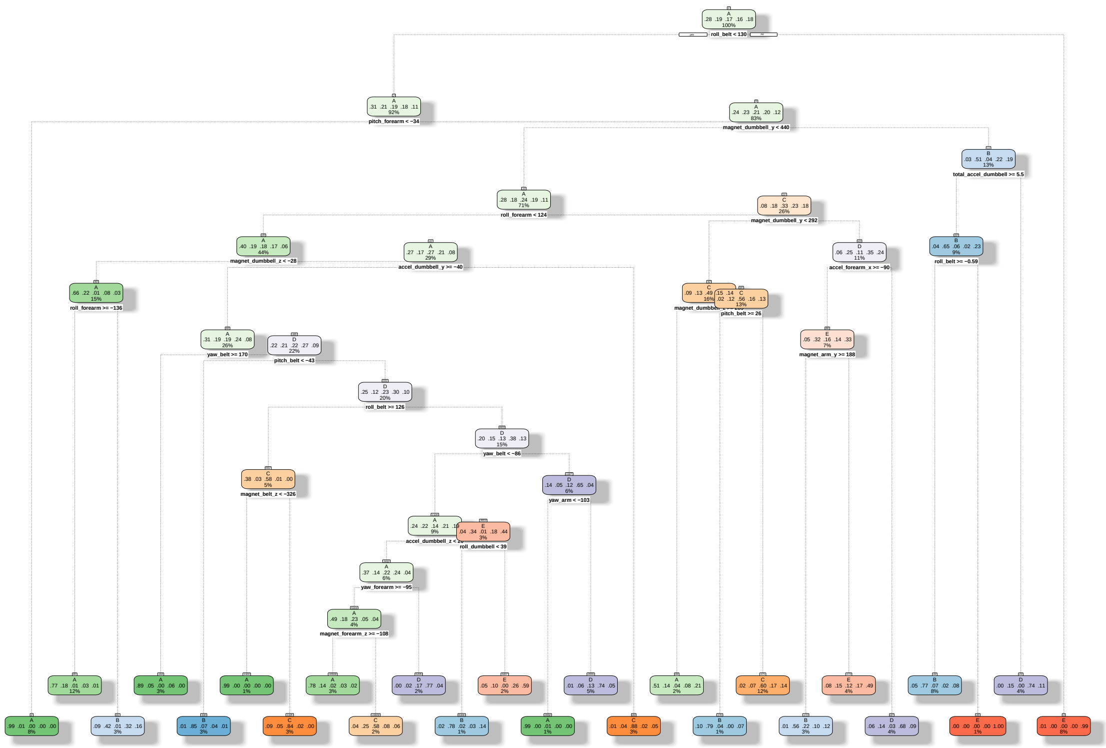
Model 1: Decision tree

```
dec_tre_intr <- rpart(classe ~., data = in_train, method = "class")
```

plot of decision tree:

```
fancyRpartPlot(dec_tre_intr)
```

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



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```
predict_dt <- predict(dec_tre_intr, in_test,  type = "class")

confusionMatrix(predict_dt, in_test$classe)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1528  169   21   53   43
##          B   59  711   93   76   97
##          C   43  116  818  141  104
##          D   18   89   67  609   51
##          E   26   54   27   85  787
##
## Overall Statistics
##
##                Accuracy : 0.7567
##                  95% CI : (0.7455, 0.7676)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.6913
##  Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
##
```

```
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9128   0.6242   0.7973   0.6317   0.7274
## Specificity            0.9321   0.9315   0.9169   0.9543   0.9600
## Pos Pred Value         0.8423   0.6863   0.6694   0.7302   0.8039
## Neg Pred Value         0.9641   0.9117   0.9554   0.9297   0.9399
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2596   0.1208   0.1390   0.1035   0.1337
## Detection Prevalence   0.3082   0.1760   0.2076   0.1417   0.1664
## Balanced Accuracy      0.9224   0.7779   0.8571   0.7930   0.8437
```

Our decision tree model has an accuracy of 0.7567.

Model 2: Random Forest

```r
ran_fr_intr <- randomForest(classe ~., data = in_train, method = "class")
predict_rf <- predict(ran_fr_intr, in_test,  type = "class")

confusionMatrix(predict_rf, in_test$classe)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1673    8    0    0    0
##          B    0 1128    4    0    0
##          C    0    3 1020   12    0
##          D    0    0    2  952    3
##          E    1    0    0    0 1079
##
## Overall Statistics
##
##                Accuracy : 0.9944
##                  95% CI : (0.9921, 0.9961)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9929
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9994   0.9903   0.9942   0.9876   0.9972
## Specificity            0.9981   0.9992   0.9969   0.9990   0.9998
## Pos Pred Value         0.9952   0.9965   0.9855   0.9948   0.9991
## Neg Pred Value         0.9998   0.9977   0.9988   0.9976   0.9994
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2843   0.1917   0.1733   0.1618   0.1833
## Detection Prevalence   0.2856   0.1924   0.1759   0.1626   0.1835
## Balanced Accuracy      0.9988   0.9947   0.9955   0.9933   0.9985
```

In comparrison we see that our random forest model is more accuarate than our decision tree model (decision tree accuracy: 75.67%, random forest accuracy: 99.44%).

We will use the random forest model for our predictions.

The expected error range is: 0.9961-0.9921 = 0.004, which is less than 1%. So out of 20 different test cases, it is highly unlikely that any of our predictions will be incorrect.

Prediction

We finish by running our prediction on the original 20 test cases:

```
predict(ran_fr_intr, newdata = pml_testing)
```

```
##  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
```