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 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, we will use data from accelerometers on the belt, forearm, arm, and dumbell of 6 participants to predict the manner in which they did the exercise.

Data Processing

```
library(caret)
```

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

```
library(rpart)
library(rpart.plot)
library(randomForest)
```

```
## randomForest 4.6-10
## Type rfNews() to see new features/changes/bug fixes.
```

```
library(corrplot)
```

Download and load the Data Set

```
trainUrl <-"https://d396qusza40orc.cloudfront.net/predmachlearn/pml-train
testUrl <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testi
trainFile <- "pml-training.csv"
testFile  <- "pml-testing.csv"

if (!file.exists(trainFile)) {
  download.file(trainUrl, destfile=trainFile, method="curl")
}
if (!file.exists(testFile)) {
  download.file(testUrl, destfile=testFile, method="curl")
}

trainRaw <- read.csv("pml-training.csv")
testRaw <- read.csv("pml-testing.csv")
dim(trainRaw)
```

```
## [1] 19622   160
```

```
dim(testRaw)
```

```
## [1]  20 160
```

```
# Clean Data

sum(complete.cases(trainRaw))
```

```
## [1] 406
```

```
# Remove columns with NA
trainRaw <- trainRaw[, colSums(is.na(trainRaw)) == 0]
testRaw <- testRaw[, colSums(is.na(testRaw)) == 0]

# Remove redundant columns
classe <- trainRaw$classe
trainRemove <- grepl("^X|timestamp|window", names(trainRaw))
trainRaw <- trainRaw[, !trainRemove]
trainCleaned <- trainRaw[, sapply(trainRaw, is.numeric)]
trainCleaned$classe <- classe
testRemove <- grepl("^X|timestamp|window", names(testRaw))
testRaw <- testRaw[, !testRemove]
testCleaned <- testRaw[, sapply(testRaw, is.numeric)]

# Partition the Dataset into 70% training set and 30% validataion data se
set.seed(235)
inTrain <- createDataPartition(trainCleaned$classe, p=0.70, list=F)
trainData <- trainCleaned[inTrain, ]
testData <- trainCleaned[-inTrain, ]
```

Data Model

We fit a predictive model for activity recognition using Random Forest algorithm because it automatically selects important variables and is robust to correlated covariates & outliers in general. We will use 5-fold cross validation when applying the algorithm.

```
controlRf <- trainControl(method="cv", 5)
modelRf <- train(classe ~ ., data=trainData, method="rf", trControl=contr
modelRf
```

```
## 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, 10989, 10991, 10988, 10991
##
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa      Accuracy SD   Kappa SD
##    2    0.9898089  0.9871081  0.0028982632  0.003665981
##   27    0.9905366  0.9880283  0.0009271304  0.001171553
##   52    0.9858046  0.9820411  0.0024166419  0.003059055
##
## Accuracy was used to select the optimal model using  the largest value
## The final value used for the model was mtry = 27.
```

We estimate the performance of the model on the validation data set.

```
predictRf <- predict(modelRf, testData)
confusionMatrix(testData$classe, predictRf)
```

```
## Confusion Matrix and Statistics
## 
##           Reference
## Prediction    A    B    C    D    E
##          A 1669    2    2    0    1
##          B    9 1129    1    0    0
##          C    0    5 1017    4    0
##          D    0    0   12  952    0
##          E    0    1    0    2 1079
## 
## Overall Statistics
##                                           
##                Accuracy : 0.9934          
##                  95% CI : (0.991, 0.9953)
##     No Information Rate : 0.2851          
##     P-Value [Acc > NIR] : < 2.2e-16       
##                                           
##                   Kappa : 0.9916          
##  Mcnemar's Test P-Value : NA              
## 
## Statistics by Class:
## 
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9946   0.9930   0.9855   0.9937   0.9991
## Specificity            0.9988   0.9979   0.9981   0.9976   0.9994
## Pos Pred Value         0.9970   0.9912   0.9912   0.9876   0.9972
## Neg Pred Value         0.9979   0.9983   0.9969   0.9988   0.9998
## Prevalence             0.2851   0.1932   0.1754   0.1628   0.1835
## Detection Rate         0.2836   0.1918   0.1728   0.1618   0.1833
## Detection Prevalence   0.2845   0.1935   0.1743   0.1638   0.1839
## Balanced Accuracy      0.9967   0.9954   0.9918   0.9957   0.9992
```

```
accuracy <- postResample(predictRf, testData$classe)
accuracy
```

```
##  Accuracy     Kappa 
## 0.9933730 0.9916169
```

```
oose <- 1 - as.numeric(confusionMatrix(testData$classe, predictRf)$overal
oose
```

```
## [1] 0.006627018
```

```
# The estimated accuracy of the model is 99.42% and the estimated out-of-
```

Predict the Test Data Set

We apply the model to the original testing data set with the problem_id column removed.

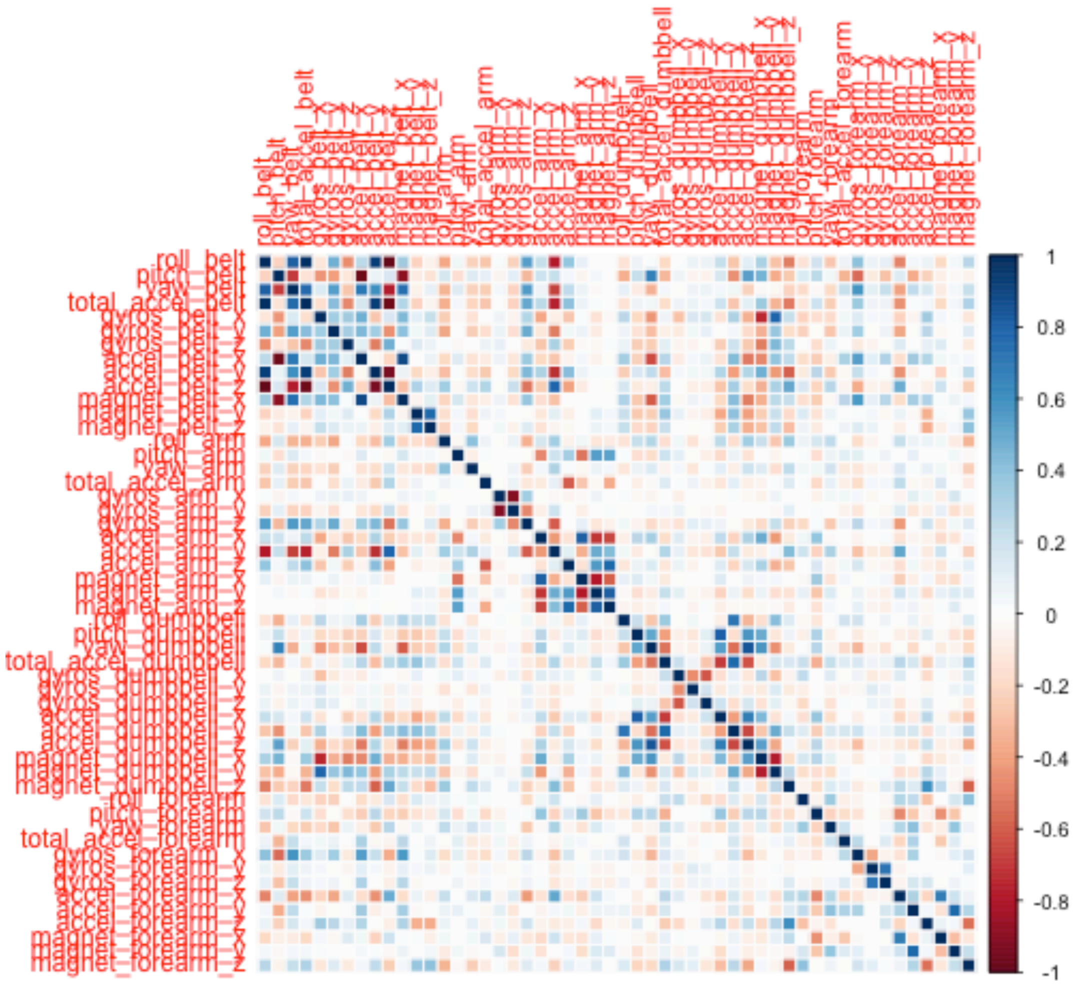
```
result <- predict(modelRf, testCleaned[, -length(names(testCleaned))])
result
```

```
##  [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
```

Figures

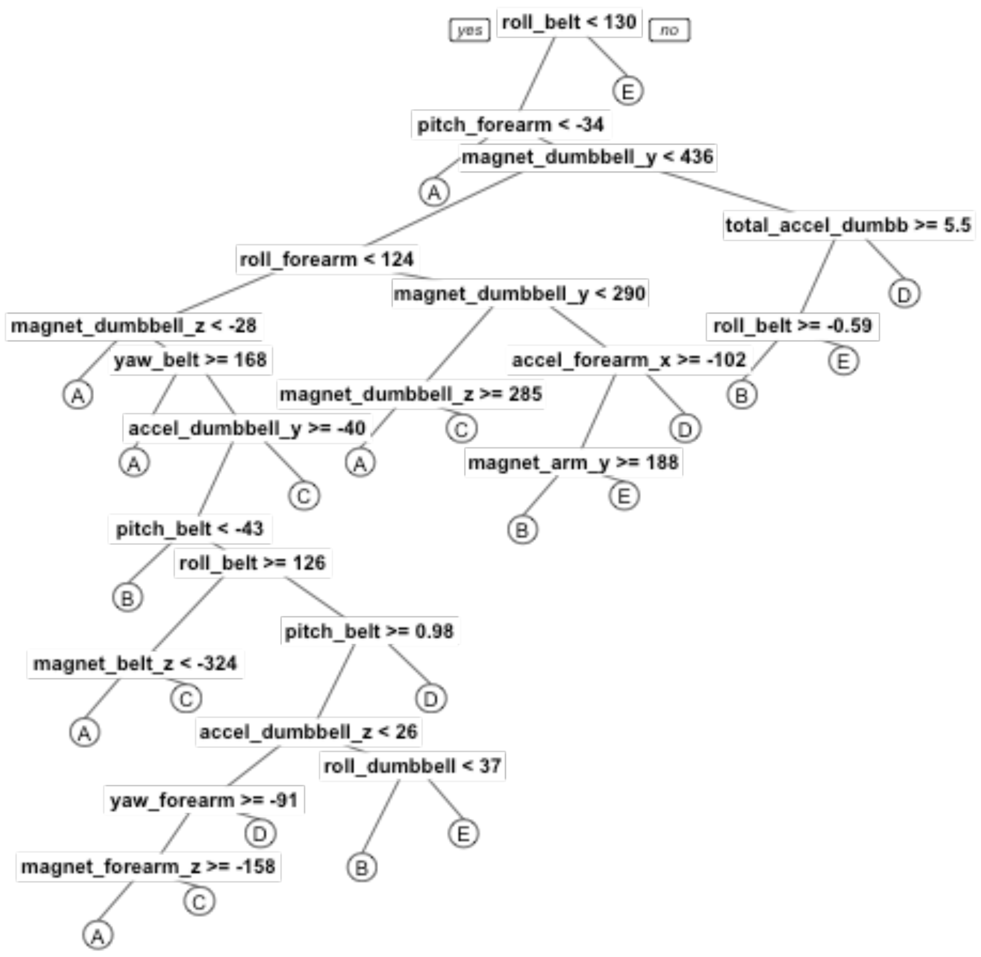
1) Correlation Matrix Visualization

```
corrPlot <- cor(trainData[, -length(names(trainData))])
corrplot(corrPlot, method="color")
```



2) Decision Tree Visualization

```
treeModel <- rpart(classe ~ ., data=trainData, method="class")
prp(treeModel) # fast plot
```


yes
roll_belt < 130
no
E
pitch_forearm < -34
magnet_dumbbell_y < 436
A
total_accel_dumbb >= 5.5
roll_forearm < 124
magnet_dumbbell_y < 290
D
magnet_dumbbell_z < -28
yaw_belt >= 168
roll_belt >= -0.59
accel_forearm_x >= -102
E
A
magnet_dumbbell_z >= 285
B
accel_dumbbell_y >= -40
C
D
A
A
magnet_arm_y >= 188
C
E
pitch_belt < -43
B
roll_belt >= 126
B
pitch_belt >= 0.98
magnet_belt_z < -324
C
D
A
accel_dumbbell_z < 26
roll_dumbbell < 37
yaw_forearm >= -91
D
E
magnet_forearm_z >= -158
B
C
A