PML_project

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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, 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.

Data Loading

```
suppressWarnings(library(dplyr))
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
suppressWarnings(library(ggplot2))
suppressWarnings(library(lubridate))
```

```
##
## Attaching package: 'lubridate'
```

```
## The following object is masked from 'package:base':
##
##     date
```

```
suppressWarnings(library(caret))
```

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

```
suppressWarnings(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:ggplot2':
##
##     margin
```

```
## The following object is masked from 'package:dplyr':
##
##     combine
```

```
suppressWarnings(library(rpart))
suppressWarnings(library(rpart.plot))
suppressWarnings(library(corrplot))
```

```
## corrplot 0.84 loaded
```

```
data.train<- read.csv("C:/Users/Sergio Rodriguez/Documents/Coursera/Practical Machine Learning/p
ml-training.csv", na.strings = c("NA", "#DIV/0!", ""))

data.test<- read.csv("C:/Users/Sergio Rodriguez/Documents/Coursera/Practical Machine Learning/pm
l-testing.csv", na.strings = c("NA", "#DIV/0!", ""))
```

Data Transformation

Understand the data, convert date and add a new varaible day.

```
dim(data.train)
```

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

```
data.train$cvtd_timestamp<- as.Date(data.train$cvtd_timestamp, format = "%m/%d/%Y %H:%M")
data.train$Day<-factor(weekdays(data.train$cvtd_timestamp)) #Add day variable

table(data.train$classe)
```

```
##
##    A    B    C    D    E
## 5580 3797 3422 3216 3607
```

```
prop.table(table(data.train$classe))
```

```
##
##         A         B         C         D         E
## 0.2843747 0.1935073 0.1743961 0.1638977 0.1838243
```

```
prop.table(table(data.train$user_name))
```

```
##
##    adelmo  carlitos   charles    eurico    jeremy     pedro
## 0.1983488 0.1585975 0.1802059 0.1564570 0.1733768 0.1330140
```

```
prop.table(table(data.train$user_name,data.train$classe),1)
```

```
##
##                    A         B         C         D         E
##   adelmo   0.2993320 0.1993834 0.1927030 0.1323227 0.1762590
##   carlitos 0.2679949 0.2217224 0.1584190 0.1561697 0.1956941
##   charles  0.2542421 0.2106900 0.1524321 0.1815611 0.2010747
##   eurico   0.2817590 0.1928339 0.1592834 0.1895765 0.1765472
##   jeremy   0.3459730 0.1437390 0.1916520 0.1534392 0.1651969
##   pedro    0.2452107 0.1934866 0.1911877 0.1796935 0.1904215
```

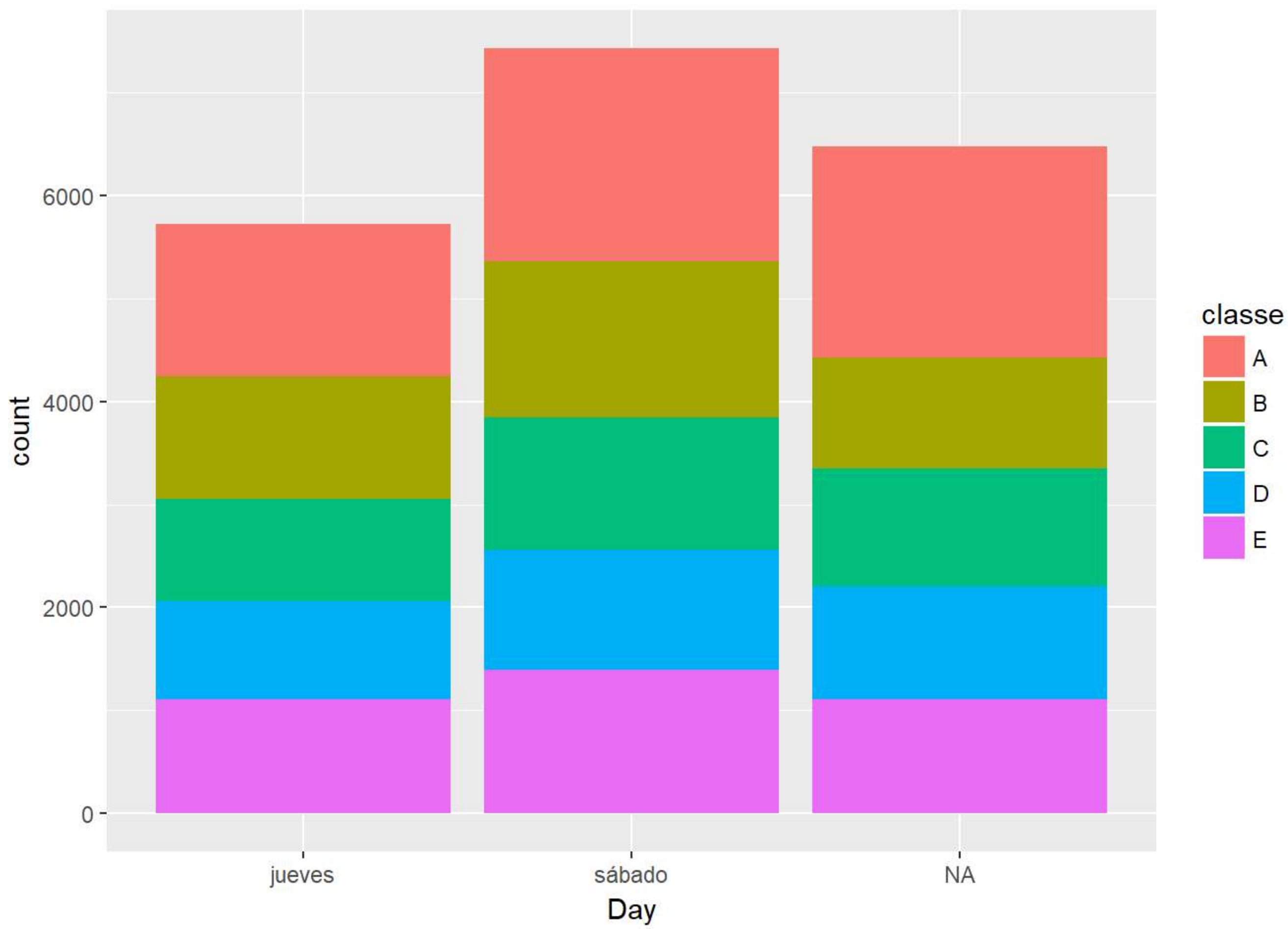
```
prop.table(table(data.train$user_name,data.train$classe),2)
```

```
##
##                    A         B         C         D         E
##   adelmo   0.2087814 0.2043719 0.2191701 0.1601368 0.1901857
##   carlitos 0.1494624 0.1817224 0.1440678 0.1511194 0.1688384
##   charles  0.1611111 0.1962075 0.1575102 0.1996269 0.1971167
##   eurico   0.1550179 0.1559126 0.1428989 0.1809701 0.1502634
##   jeremy   0.2109319 0.1287859 0.1905319 0.1623134 0.1558082
##   pedro    0.1146953 0.1329997 0.1458212 0.1458333 0.1377876
```

```
prop.table(table(data.train$classe, data.train$Day),1)
```

```
##
##        jueves    sábado
##    A 0.4166196 0.5833804
##    B 0.4399853 0.5600147
##    C 0.4348970 0.5651030
##    D 0.4521780 0.5478220
##    E 0.4418698 0.5581302
```

```
qplot(x=Day, fill=classe, data = data.train)
```



Data Cleaning

```
# Remove columns with NA missing values
data.train <- data.train[, colSums(is.na(data.train)) == 0]
data.test <- data.test[, colSums(is.na(data.test)) == 0]

# Remove columns that are not relevant to accelerometer measurements.
classe<- data.train$classe
trainRemove<- grepl("^X|timestamp|window", names(data.train))
data.train<- data.train[, !trainRemove]
trainCleaned<- data.train[, sapply(data.train, is.numeric)]
trainCleaned$classe<- classe
testRemove<- grepl("^X|timestamp|window", names(data.test))
data.test<- data.test[, !testRemove]
testCleaned<- data.test[, sapply(data.test, is.numeric)]
```

Create Train and Test Data Sets

```
set.seed(22519)
inTrain <- createDataPartition(trainCleaned$classe, p=0.70, list=F)
trainData <- trainCleaned[inTrain, ]
testData <- trainCleaned[-inTrain, ]
```

Data Modelling

```
controlRf <- trainControl(method="cv", 5)
rfmod<- train(classe ~., data=trainData, method="rf", trControl=controlRf, importance=TRUE, ntre
e=100)
rfmod
```

```
## 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, 10991, 10988, 10989, 10991
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa
##    2    0.9902446  0.9876590
##   27    0.9911181  0.9887647
##   52    0.9852942  0.9813962
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 27.
```

Accuracy of Model

```
predictRfmod<- predict(rfmod, testData)
confusionMatrix(testData$classe, predictRfmod)
```

```
## Confusion Matrix and Statistics
## 
##           Reference
## Prediction    A    B    C    D    E
##          A 1673    0    0    0    1
##          B    7 1128    4    0    0
##          C    0    0 1021    5    0
##          D    0    0   13  950    1
##          E    0    0    1    7 1074
## 
## Overall Statistics
## 
##                Accuracy : 0.9934
##                  95% CI : (0.991, 0.9953)
##     No Information Rate : 0.2855
##     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            0.9958   1.0000   0.9827   0.9875   0.9981
## Specificity            0.9998   0.9977   0.9990   0.9972   0.9983
## Pos Pred Value         0.9994   0.9903   0.9951   0.9855   0.9926
## Neg Pred Value         0.9983   1.0000   0.9963   0.9976   0.9996
## Prevalence             0.2855   0.1917   0.1766   0.1635   0.1828
## Detection Rate         0.2843   0.1917   0.1735   0.1614   0.1825
## Detection Prevalence   0.2845   0.1935   0.1743   0.1638   0.1839
## Balanced Accuracy      0.9978   0.9988   0.9908   0.9923   0.9982
```

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

```
## Accuracy    Kappa 
## 0.993373 0.991617
```

```
Error <- 1 - as.numeric(confusionMatrix(testData$classe, predictRfmod)$overall[1])
Error
```

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

So, the estimated accuracy of the model is 99.32% and the estimated out-of-sample error is 0.68%.

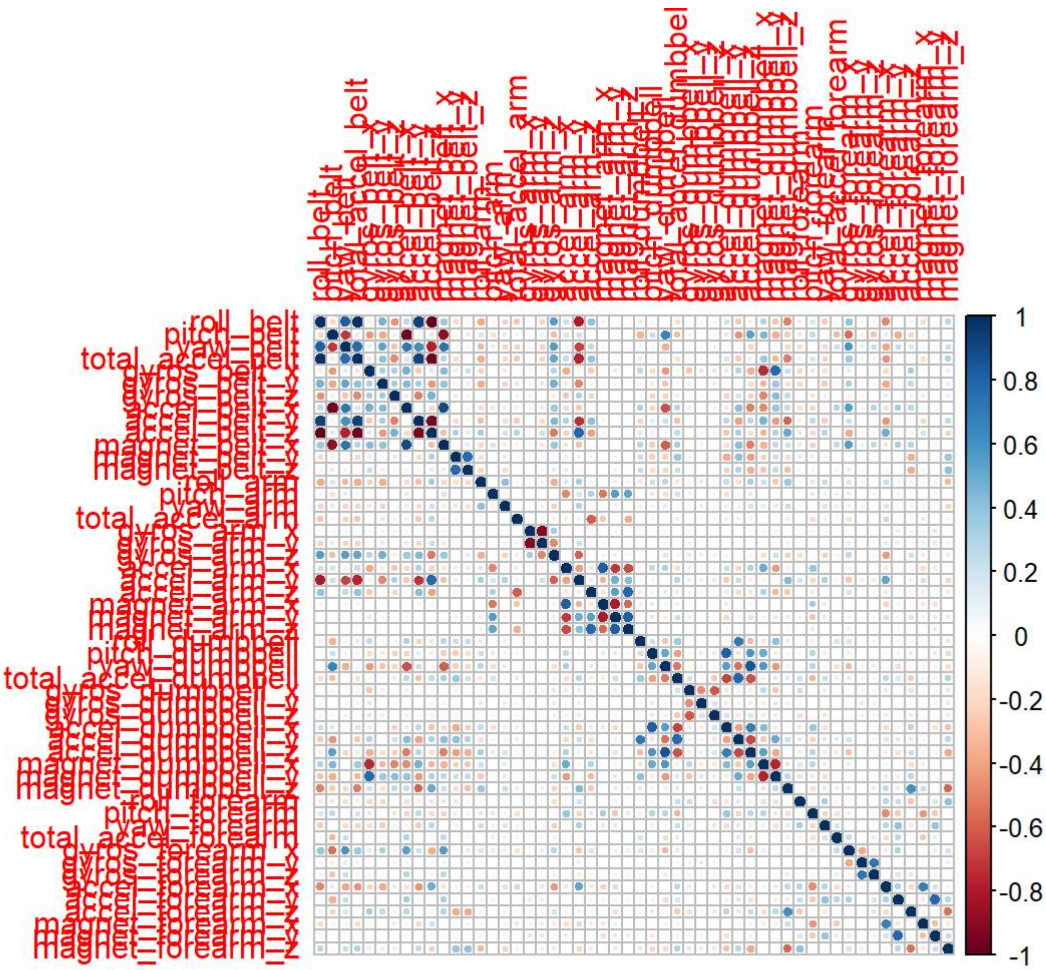
Predicting on test Data

```
result <- predict(rfmod, 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
```

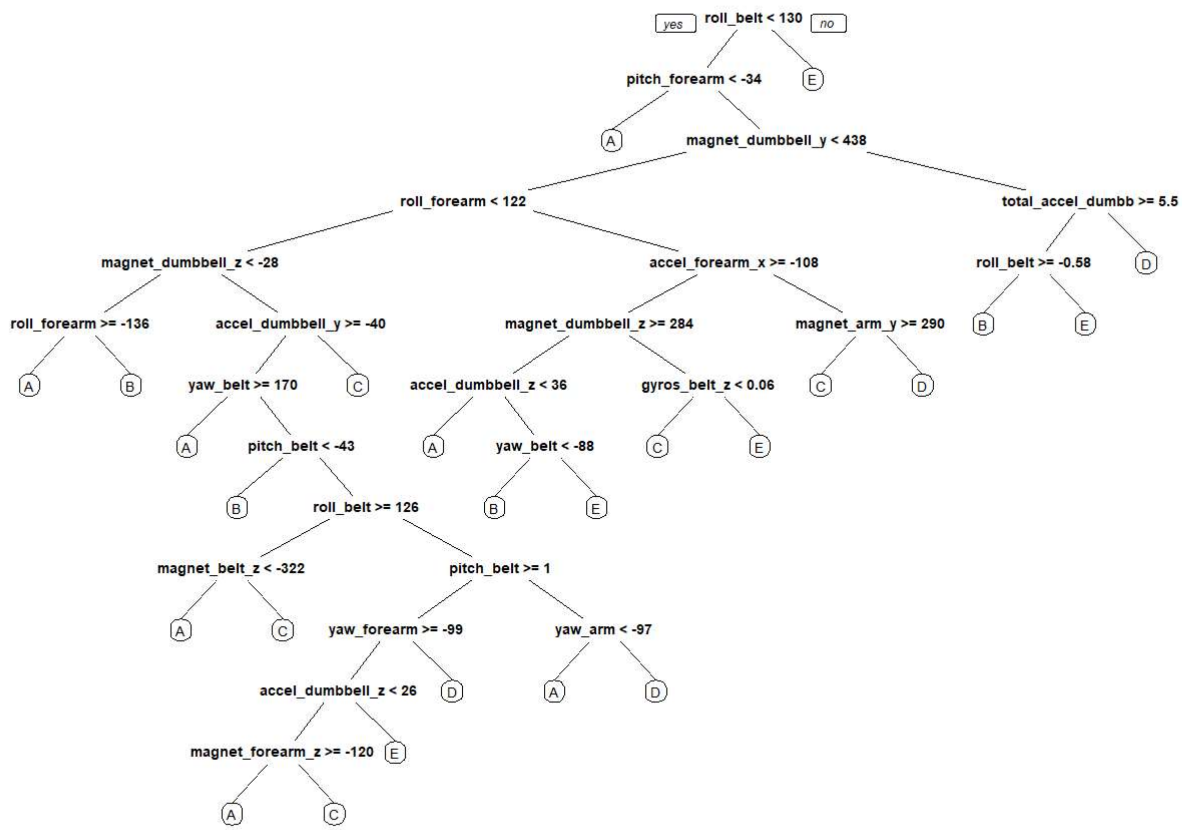
Correlation MAtrix

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



Tree Visualization

```
rtree<- rpart(classe ~ ., data=trainData, method="class")
prp(rtree)
```


yes
roll_belt < 130
no
pitch_forearm < -34
E
A
magnet_dumbbell_y < 438
roll_forearm < 122
total_accel_dumbb >= 5.5
magnet_dumbbell_z < -28
accel_forearm_x >= -108
roll_belt >= -0.58
D
roll_forearm >= -136
accel_dumbbell_y >= -40
magnet_dumbbell_z >= 284
magnet_arm_y >= 290
B
E
A
B
yaw_belt >= 170
C
accel_dumbbell_z < 36
gyros_belt_z < 0.06
C
D
A
pitch_belt < -43
A
yaw_belt < -88
C
E
B
roll_belt >= 126
B
E
magnet_belt_z < -322
pitch_belt >= 1
A
C
yaw_forearm >= -99
yaw_arm < -97
accel_dumbbell_z < 26
D
A
D
magnet_forearm_z >= -120
E
A
C