Title: Machine Learning Course Project

Background inforamtion:

Six participants wearing accelerometers on their belt, forearm, arm, and dumbell were asked to perform barbell lifts correctly and incorrectly in 5 different ways. Our goal is to predict the manner in which they did the exercise. Both training and testing data sets are from the website: http://groupware.les.inf.puc-rio.br/har

Load library

```
FALSE
FALSE Attaching package: 'dplyr'

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

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

FALSE Loading required package: lattice

FALSE Loading required package: ggplot2

FALSE Rattle: A free graphical interface for data mining with R.
FALSE Version 4.1.0 Copyright (c) 2006-2015 Togaware Pty Ltd.
FALSE Type 'rattle()' to shake, rattle, and roll your data.

FALSE ------------------------------------------------------------------------

FALSE data.table + dplyr code now lives in dtplyr.
FALSE Please library(dtplyr)!

FALSE ------------------------------------------------------------------------

FALSE
FALSE Attaching package: 'data.table'

FALSE The following objects are masked from 'package:dplyr':
FALSE
FALSE     between, first, last
```

Data source

```r
url <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
training <- fread(url)

url <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"
testing <- fread(url)
```

Data cleaning.

Remove variables with all missing values. Remove ID varaibles.

```r
isAnyMissing <- sapply(training, function (x) any(is.na(x) | x == ""))
keepVariable <- names(isAnyMissing)[!isAnyMissing]
keepVariable <- keepVariable[-c(1,2)]
```

subset primary dataset with only related varialbes and outcome varialbe classe.

```r
trainSet <- select_(training, .dots = keepVariable)
testSet <- select_(testing, .dots = keepVariable[-58])
```

Create training and testing

```r
set.seed(1234)
inTrain = createDataPartition(trainSet$classe, p = 0.6)[[1]]
myTraining = trainSet[ inTrain,]
myTesting = trainSet[-inTrain,]
```

Building models

Method: random forest

```r
set.seed(1234)
controlRF <- trainControl(method="cv", number=3, verboseIter=FALSE)
modelRF <- train(classe ~ ., data=myTraining, method="rf", trControl=controlRF)
```

```
## Loading required package: randomForest

## 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

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

```r
modelRF$finalModel
```

```
##
## Call:
##  randomForest(x = x, y = y, mtry = param$mtry)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 38
##
##         OOB estimate of  error rate: 0.17%
## Confusion matrix:
```

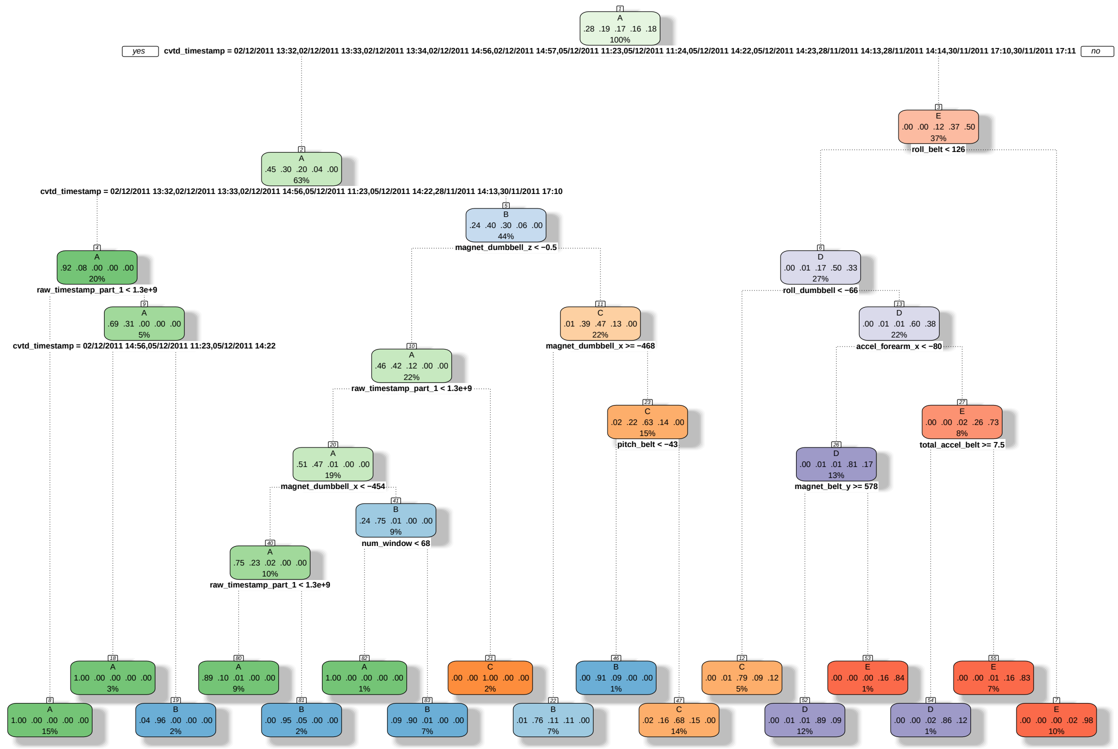
```
##      A    B    C    D    E  class.error
## A 3348    0    0    0    0 0.0000000000
## B    4 2273    2    0    0 0.0026327337
## C    0    3 2047    4    0 0.0034079844
## D    0    0    3 1925    2 0.0025906736
## E    0    0    0    2 2163 0.0009237875
```

```r
predictRF <- predict(modelRF, newdata=myTesting)
confMatRF<- confusionMatrix(predictRF, myTesting$classe)
confMatRF
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 2232    2    0    0    0
##          B    0 1516    1    0    0
##          C    0    0 1367    3    0
##          D    0    0    0 1283    0
##          E    0    0    0    0 1442
##
## Overall Statistics
##
##                Accuracy : 0.9992
##                  95% CI : (0.9983, 0.9997)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.999
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   0.9987   0.9993   0.9977   1.0000
## Specificity            0.9996   0.9998   0.9995   1.0000   1.0000
## Pos Pred Value         0.9991   0.9993   0.9978   1.0000   1.0000
## Neg Pred Value         1.0000   0.9997   0.9998   0.9995   1.0000
## Prevalence             0.2845   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2845   0.1932   0.1742   0.1635   0.1838
## Detection Prevalence   0.2847   0.1933   0.1746   0.1635   0.1838
## Balanced Accuracy      0.9998   0.9993   0.9994   0.9988   1.0000
```

Method: Decision Trees

```r
set.seed(1234)
modelDT <- rpart(classe ~ ., data=myTraining, method="class")
fancyRpartPlot(modelDT)
```



Rattle 2017−Apr−07 19:48:26 lanjblue

```r
predictDT <- predict(modelDT, newdata=myTesting, type="class")
confMatDT <- confusionMatrix(predictDT, myTesting$classe)
confMatDT
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 2161   61    5    3    0
##          B   50 1271   95   64    0
##          C   21  177 1242  203   65
##          D    0    9   19  899   92
##          E    0    0    7  117 1285
##
## Overall Statistics
##
##                Accuracy : 0.8741
##                  95% CI : (0.8665, 0.8813)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.8407
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9682   0.8373   0.9079   0.6991   0.8911
## Specificity            0.9877   0.9670   0.9281   0.9817   0.9806
```

```
## Pos Pred Value         0.9691   0.8588   0.7272   0.8822   0.9120
## Neg Pred Value         0.9874   0.9612   0.9795   0.9433   0.9756
## Prevalence             0.2845   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2754   0.1620   0.1583   0.1146   0.1638
## Detection Prevalence   0.2842   0.1886   0.2177   0.1299   0.1796
## Balanced Accuracy      0.9779   0.9021   0.9180   0.8404   0.9359
```

Method: Generalized Boosted Model

```r
set.seed(1234)
controlGBM <- trainControl(method = "repeatedcv", number = 5, repeats = 1)
modelGBM  <- train(classe ~ ., data=myTraining, method = "gbm",
                   trControl = controlGBM, verbose = FALSE)
```

```
## Loading required package: gbm

## Loading required package: survival

##
## Attaching package: 'survival'

## The following object is masked from 'package:caret':
##
##     cluster

## Loading required package: splines

## Loading required package: parallel

## Loaded gbm 2.1.3

## Loading required package: plyr

## --------------------------------------------------------------------------

## You have loaded plyr after dplyr - this is likely to cause problems.
## If you need functions from both plyr and dplyr, please load plyr first, then dplyr:
## library(plyr); library(dplyr)

## --------------------------------------------------------------------------

##
## Attaching package: 'plyr'

## The following objects are masked from 'package:dplyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize
```

```r
modelGBM$finalModel
```

```
## A gradient boosted model with multinomial loss function.
## 150 iterations were performed.
## There were 75 predictors of which 45 had non-zero influence.
```

```r
predictGBM <- predict(modelGBM, newdata=myTesting)
confMatGBM <- confusionMatrix(predictGBM, myTesting$classe)
confMatGBM
```

```
## Confusion Matrix and Statistics
##
```

```
##           Reference
## Prediction    A    B    C    D    E
##          A 2232    3    0    0    0
##          B    0 1511    4    0    0
##          C    0    4 1351    7    0
##          D    0    0   13 1275    2
##          E    0    0    0    4 1440
##
## Overall Statistics
##
##                Accuracy : 0.9953
##                  95% CI : (0.9935, 0.9967)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.994
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   0.9954   0.9876   0.9914   0.9986
## Specificity            0.9995   0.9994   0.9983   0.9977   0.9994
## Pos Pred Value         0.9987   0.9974   0.9919   0.9884   0.9972
## Neg Pred Value         1.0000   0.9989   0.9974   0.9983   0.9997
## Prevalence             0.2845   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2845   0.1926   0.1722   0.1625   0.1835
## Detection Prevalence   0.2849   0.1931   0.1736   0.1644   0.1840
## Balanced Accuracy      0.9997   0.9974   0.9929   0.9946   0.9990
```

Which model is more accurate

Comparing the three modesl used here: random forest, decision tree and generalized boosted model, we can see that random forest yield better accuracy. Thus we will use it to further predict our testing set.

```
confMatRF$overall[1]
```

```
##  Accuracy
## 0.9992353
```

```
confMatDT$overall[1]
```

```
## Accuracy
## 0.874076
```

```
confMatGBM$overall[1]
```

```
##  Accuracy
## 0.9952842
```

Making Test Set Predictions.

```
predictTEST <- predict(modelRF, newdata=testing)
predictTEST
```

```
##  [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
```