Practical Machine Learning Course Project

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Human Activity Recognition - Predicting Weight Lifting Exercise Correctness

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. 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, the goal is 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 (see the section on the Weight Lifting Exercise Dataset).

About Dataset

The data for this project come from http://groupware.les.inf.puc-rio.br/har. I heartfully thank the generousity of the website for providing the data for this research project.

Objective

The Objective is to predict the manner in which the exercise is done. This is the "classe" variable in the training set. Describe how model is built, cross-validated, and how out of sample error is calculated. Lastly, predict 20 different test cases using prediction model.

Data Pre-Processing

Downloading the datasets

```
trainurl <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
testurl <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"

setInternet2(FALSE)
f_train <- "pml-training.csv"
if(!file.exists(f_train)) {
    download.file(url=trainurl,destfile = f_train, mode = "wb")
}

f_test <- "pml-testing.csv"
if(!file.exists(f_test)) {
    download.file(url=testurl,destfile = f_test, mode = "wb")
}

#### Read the Data File
```

```r
training <- read.csv(f_train, na.strings=c("NA",""))

### Exploratory Analysis
table(colSums(is.na(training)))
```

```
##
##     0 19216
##    60   100
```

Means there are 60 columns with no NAs and 100 columns with 19216 (~98%) NAs out of 19622 rows. So, we simply remove those columns with 98% NAs.

Cleaning the data

```r
training <- training[, colSums(is.na(training)) == 0]   # Keeping predictors without NAs
```

Removing the first seven predictors, as index, name, date-time stamp are obviously unrelated to the outcome classe

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

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

The cleaned data set trainData has 53 columns and 19622 rows with the last variable classe

Partioning the training set for cross-validation

In order to estimate the out-of-sample-error through cross-validation, it requires the training dataset to be partitioned into training and validation set. Since we already have sufficient training data (~19000 sample rows), we can keep 10% for validation and rest for training data. Count of 1900 samples for validation is fairly fine to estimate the out-of-sample-error.

```r
library(caret)
set.seed(10)
inTrain <- createDataPartition(trainData$classe, p = 0.9, list = FALSE)
trainset <- trainData[inTrain, ]
validationset <- trainData[-inTrain, ]
dim(trainset); dim(validationset)
```

```
## [1] 17662    53
```

```
## [1] 1960   53
```

Prediction Modelling

This is a typical case of classification modelling. So we will try a Decision tree and Random forest for modelling.

Decision Tree

We will choose a k-fold cross validation with k being 4 (default is 10). Here, the number of folds equal 4 and number of resampling iterations (or repeats) is equal to 1 (default). It will hopefully generate a reasonably good predictive algorithm on the cost of taking a little less time in comparison to what it would have taken with default values. Since data transformations may be less important in non-linear models like decision trees, we do not transform any variables.

```
library(rpart)
control <- trainControl(method = "cv", number = 4)
dt_model <- train(classe ~ ., data = trainset, method = "rpart", trControl = control)
dt_model
```

```
## CART
##
## 17662 samples
##    52 predictor
##     5 classes: 'A', 'B', 'C', 'D', 'E'
##
## No pre-processing
## Resampling: Cross-Validated (4 fold)
## Summary of sample sizes: 13247, 13245, 13247, 13247
## Resampling results across tuning parameters:
##
##   cp          Accuracy   Kappa
##   0.03544304  0.5232141  0.38199628
##   0.05936181  0.3965614  0.17644617
##   0.11471519  0.3240246  0.06069239
##
## Accuracy was used to select the optimal model using  the largest value.
## The final value used for the model was cp = 0.03544304.
```

It is evident that decision tree is performing poorly on the training data itself. Still no harm in verifying the accuracy from the validation data.

```
# predict outcomes using validation set
dt_prediction <- predict(dt_model, validationset)
# Show prediction result
dt_cm <- confusionMatrix(dt_prediction, validationset$classe)
dt_cm
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   A   B   C   D   E
##          A 510 145 162 133  53
##          B   4 146  10  65  44
##          C  40  88 170 123  92
##          D   0   0   0   0   0
##          E   4   0   0   0 171
##
## Overall Statistics
##
##                Accuracy : 0.5087
##                  95% CI : (0.4863, 0.531)
##     No Information Rate : 0.2847
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.3583
##  Mcnemar's Test P-Value : NA
```

```
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9140  0.38522  0.49708   0.0000  0.47500
## Specificity            0.6484  0.92220  0.78801   1.0000  0.99750
## Pos Pred Value         0.5085  0.54275  0.33138      NaN  0.97714
## Neg Pred Value         0.9498  0.86221  0.88113   0.8362  0.89412
## Prevalence             0.2847  0.19337  0.17449   0.1638  0.18367
## Detection Rate         0.2602  0.07449  0.08673   0.0000  0.08724
## Detection Prevalence   0.5117  0.13724  0.26173   0.0000  0.08929
## Balanced Accuracy      0.7812  0.65371  0.64254   0.5000  0.73625
```

Accuracy through confusion matrix is depicting to be 0.5086735, which is pretty poor. The out-of-sample error in decision tree case is 0.4913265. So, let's try Random Forests.

Random Forest

Here also training with cross-validation with K-Fold (k=4) and repeat=1.

```
library(randomForest)
```

```
## randomForest 4.6-10

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:ggplot2':
##
##     margin
```

```
#rf_model <- randomForest(classe ~ ., data = trainset) # provision for setting ntree & mtry,
                                                       # but no provision for K-fold cross-validation
rf_model <- train(classe ~ ., data = trainset, method = "rf", trControl = control)
rf_model
```

```
## Random Forest
##
## 17662 samples
##    52 predictor
##     5 classes: 'A', 'B', 'C', 'D', 'E'
##
## No pre-processing
## Resampling: Cross-Validated (4 fold)
## Summary of sample sizes: 13247, 13249, 13245, 13245
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa
##    2    0.9923568  0.9903310
##   27    0.9921302  0.9900447
##   52    0.9878836  0.9846719
##
## Accuracy was used to select the optimal model using  the largest value.
## The final value used for the model was mtry = 2.
```

```r
rf_prediction <- predict(rf_model, validationset)
rf_cm <- confusionMatrix(rf_prediction, validationset$classe)
rf_cm
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   A   B   C   D   E
##          A 558   1   0   0   0
##          B   0 378   2   0   0
##          C   0   0 340   3   0
##          D   0   0   0 318   1
##          E   0   0   0   0 359
##
## Overall Statistics
##
##                Accuracy : 0.9964
##                  95% CI : (0.9927, 0.9986)
##     No Information Rate : 0.2847
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9955
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   0.9974   0.9942   0.9907   0.9972
## Specificity            0.9993   0.9987   0.9981   0.9994   1.0000
## Pos Pred Value         0.9982   0.9947   0.9913   0.9969   1.0000
## Neg Pred Value         1.0000   0.9994   0.9988   0.9982   0.9994
## Prevalence             0.2847   0.1934   0.1745   0.1638   0.1837
## Detection Rate         0.2847   0.1929   0.1735   0.1622   0.1832
## Detection Prevalence   0.2852   0.1939   0.1750   0.1628   0.1832
## Balanced Accuracy      0.9996   0.9980   0.9961   0.9950   0.9986
```

Random Forest's Accuracy through confusion matrix is 0.9964286, which is much better than that of Decision Tree. The out-of-sample error for Random Forest is 0.0035714. Random forests chooses a subset of predictors at each split and de-correlate them with each other. This leads to high accuracy, although this algorithm is sometimes difficult to interpret and computationally inefficient (slow).

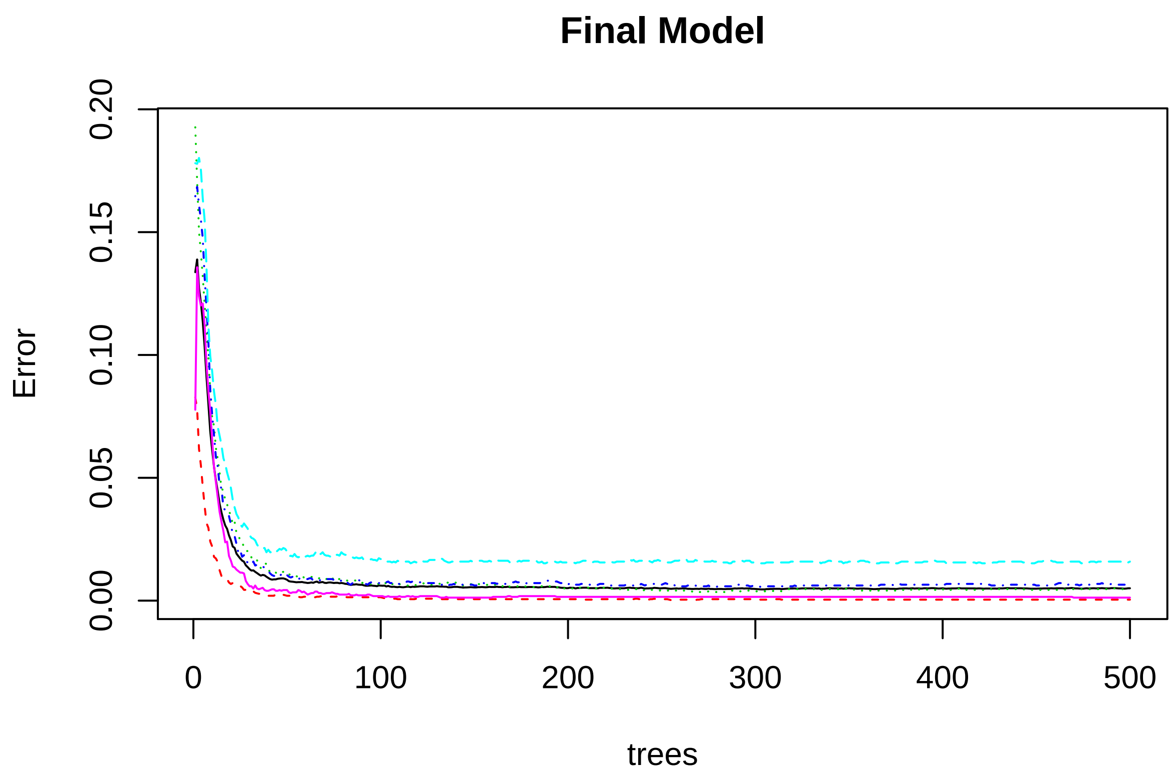
Final Model

```r
rf_model$finalModel
```

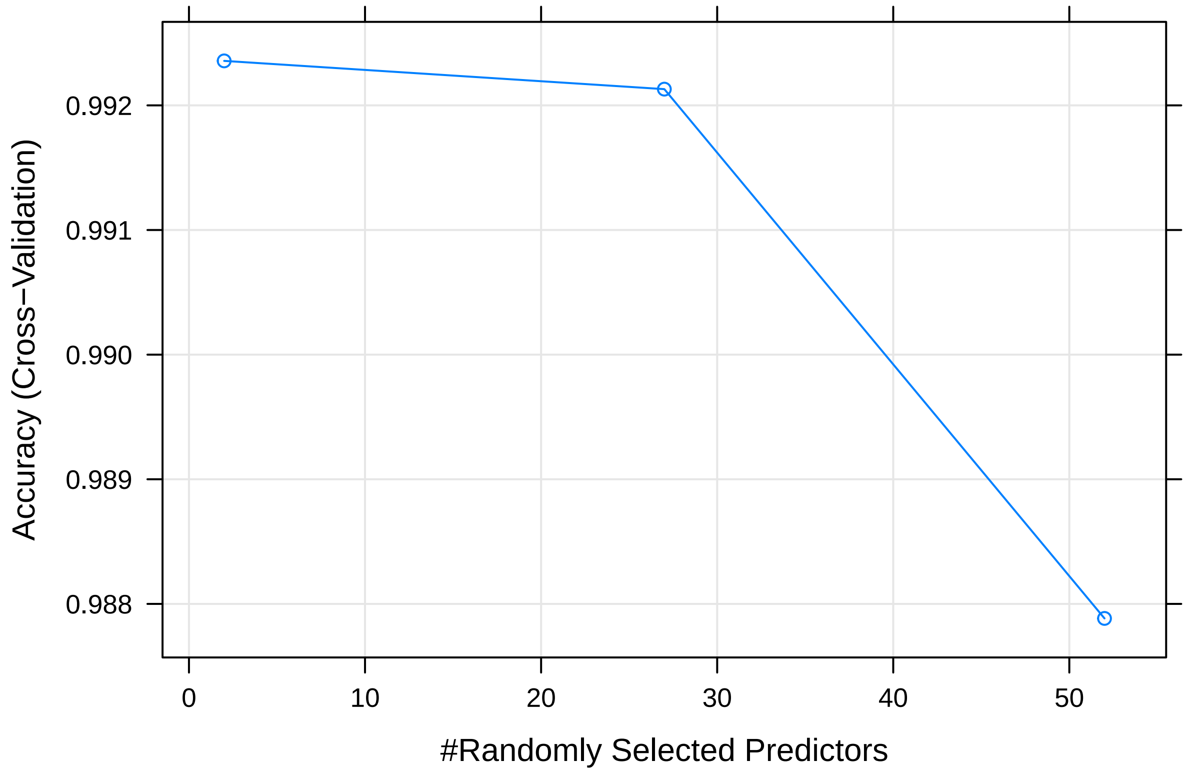
```
##
## Call:
##  randomForest(x = x, y = y, mtry = param$mtry)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 2
##
```

```
##         OOB estimate of  error rate: 0.5%
## Confusion matrix:
##      A    B    C    D    E  class.error
## A 5020    1    0    0    1 0.0003982477
## B   11 3402    5    0    0 0.0046811001
## C    0   19 3059    2    0 0.0068181818
## D    0    0   45 2849    1 0.0158894646
## E    0    0    0    4 3243 0.0012319064
```

```r
plot(rf_model$finalModel, main = "Final Model")
```




```r
plot(rf_model)
```



Predicting Test Set / Quiz

Using Random Forest model to predict test set

```r
# Reading test set data file
testing <- read.csv(f_test, na.strings=c("NA",""))
testing <- testing[, names(trainData)[1:length(trainData)-1]]   # Keep same cols for test & train
predict(rf_model, testing)
```

```
##  [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
```