Practical Machine Learning: Prediction Assignment

Ingrid Tobar

7/3/2019

1. Project Goal and Methodology

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, I use data from accelerometers on the belt, forearm, arm, and dumbell of 6 participants to predict the manner in which the participants did the exercise. At the end, the best prediction model is used to predict 20 different test cases.

Data

- TrainData: The training data for this project are available here:

https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv (https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv)

- TestData: The test data for this project are available here:

https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv (https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv)

Model Building

The outcome variable is 'classe', a factor variable with 5 levels. The study participants were asked to perform one set of 10 repetitions of unilateral dumbbell biceps curl in five different ways:

- Class A: Exactly according to the specification
- Class B: Throwing the elbows to the front
- Class C: Lifting the dumbbell only halfway
- Class D: Lowering the dumbbell only halfway
- Class E: Throwing the hips to the front

The models tested include Decision Tree and Random Forest. The model with the highest accuracy will be chosen as the final model.

Cross-validation

In order to perform cross-validation, the TrainData dataset is subsampled without replacement as follows:

- Train_TrainData: 75% of the Training dataset - Used to fit the models
- Test_TrainData: 25% of the Training dataset - Used to test the models

This process will help identify the most accurate model. That model will be tested on the TestData dataset.

Expected Out of Sample Error

The expected value of the out-of-sample error corresponds to the expected number of missclassified observations/total observations in the TestData dataset, which is equivalent to 1-accuracy found from the cross-validation data set.

2. Code and Results

Package Installation and Loading

Install and load the required packages for the analysis:

```
#install.packages("caret"); install.packages("randomForest"); install.packages("rpart");
library(lattice); library(ggplot2); library(caret); library(randomForest); library(rpart); library(rpart.plot);
```

```
## 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
```

Data Loading and Preparation

Set the seed to ensure reproducibility, load the data (previously downloaded from source), and remove NA and null values:

```
set.seed(1234)
TrainData <- read.csv("pml-training.csv", na.strings=c("NA","#DIV/0!", ""))
TestData <- read.csv("pml-testing.csv", na.strings=c("NA","#DIV/0!", ""))
```

Exploratory Analysis

Check dimensions, summary statistics (optional), and first 6 rows (optional) of TrainData:

```
dim(TrainData)
```

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

```
#summary(TrainData)
#head(TrainData)
```

Check dimensions, summary statistics (optional), and first 6 rows (optional) of TestData:

```
dim(TestData)
```

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

```
#summary(TestData)
#head(TestData)
```

Data Clean-Up

Delete any columns which contain only missing values and remove variables that are irrelevant to the model: user_name, raw_timestamp_part_1, raw_timestamp_part_,2 cvtd_timestamp, new_window, and num_window (columns 1 to 7)

```
TrainData <- TrainData[,colSums(is.na(TrainData)) == 0]
TestData <- TestData[,colSums(is.na(TestData)) == 0]
TrainData   <- TrainData[,-c(1:7)]
TestData <- TestData[,-c(1:7)]
```

Subsampling TrainData

Subsample TrainData dataset without replacement as follows:

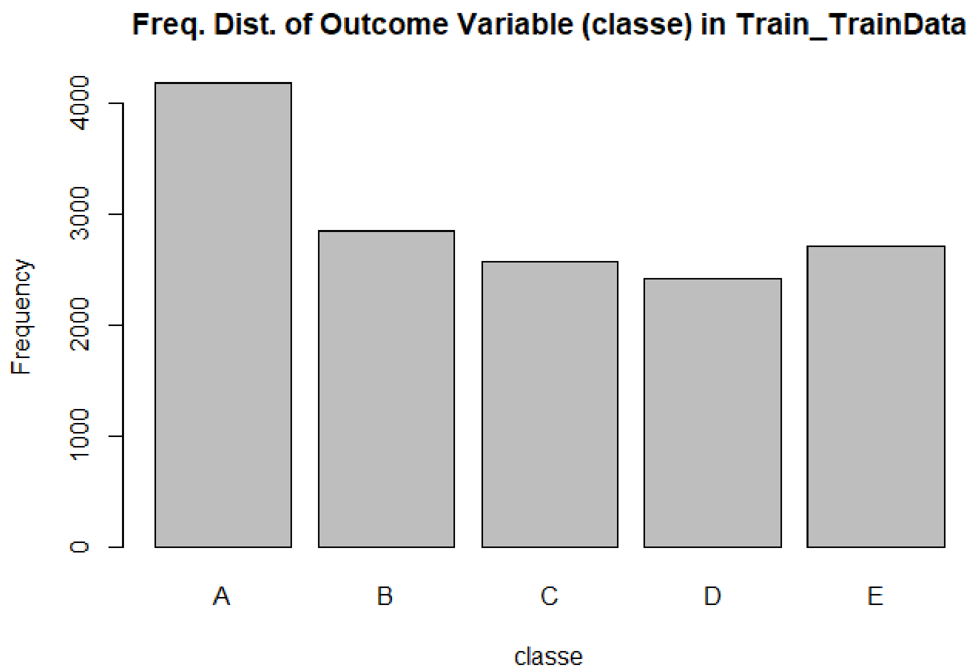
- Train_TrainData: 75% of the Training dataset - Used to fit the models
- Test_TrainData: 25% of the Training dataset - Used to test the models

```
Partition_TrainData <- createDataPartition(y=TrainData$classe, p=0.75, list=FALSE)
Train_TrainData <- TrainData[Partition_TrainData, ]
Test_TrainData <- TrainData[-Partition_TrainData, ]
```

Outcome Variable Frequency Distribution

Plot the frequency distribution of the outcome variable (“classe”) in the Train_TrainData dataset:

```
plot(Train_TrainData$classe, col="gray", main="Freq. Dist. of Outcome Variable (classe) in Train_TrainData", xlab="classe",
 ylab="Frequency")
```



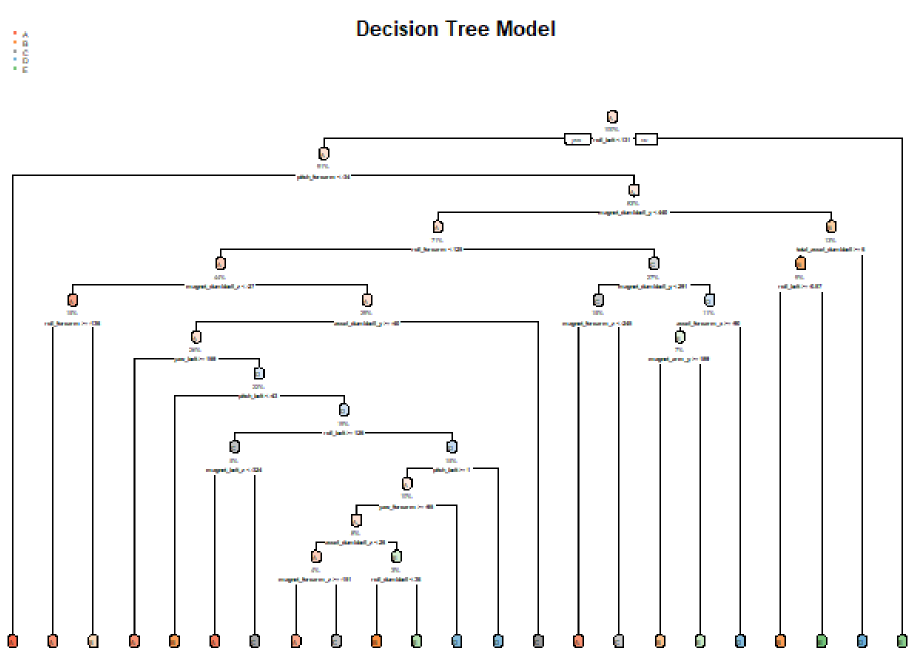
This plot shows that Outcome Variable A is the most frequent, whereas Outome Variable D is the least frequent. However, all the outcome variables are within the same order of magnitude.

3. Model Building and Evaluation

Build Decision Tree Model

Build a Decision Tree model with the Train_TrainData dataset and plot the Decision Tree

```
Model_DecTree <- rpart(classe ~ ., data=Train_TrainData, method="class")
Predict_DecTree <- predict(Model_DecTree, Test_TrainData, type = "class")
rpart.plot(Model_DecTree, main="Decision Tree Model", extra=100, under=TRUE, faclen=0)
```



Decision Tree Model Testing

Test the Decision Tree model on the Test_TrainData dataset and output the Confusion Matrix and Statistics:

```
DecTree_ConfMatrix <- confusionMatrix(Predict_DecTree, Test_TrainData$classe)
DecTree_ConfMatrix
```

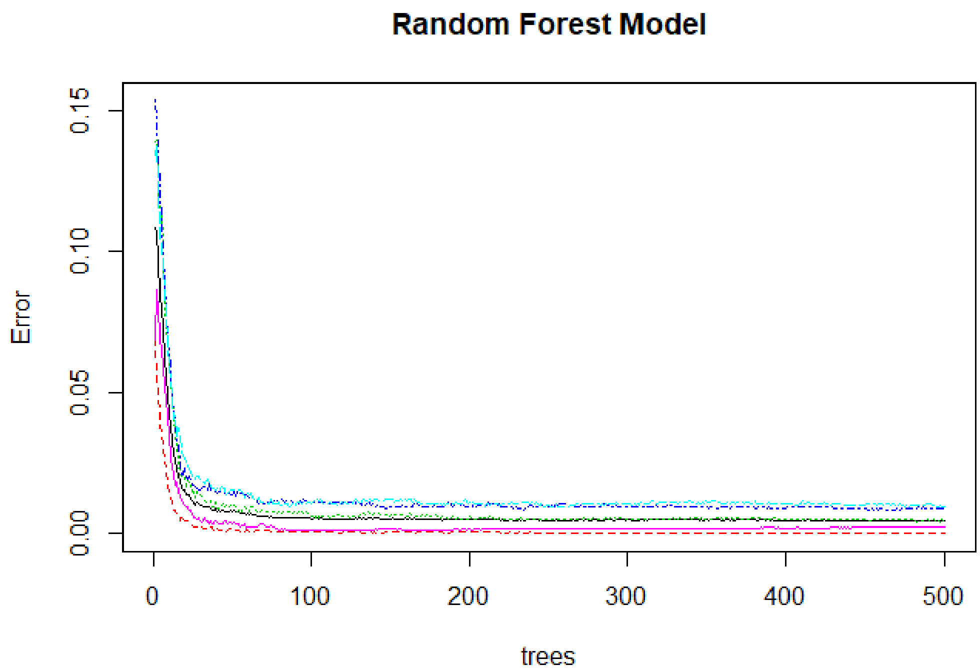
```
## Confusion Matrix and Statistics
## 
##           Reference
## Prediction    A    B    C    D    E
##          A 1251  149   15   61   17
##          B   38  572   75   60   75
##          C   39  117  696  117  122
##          D   49   58   51  508   58
##          E   18   53   18   58  629
## 
## Overall Statistics
##                                           
##                Accuracy : 0.7455          
##                  95% CI : (0.7331, 0.7577)
##     No Information Rate : 0.2845          
##     P-Value [Acc > NIR] : < 2.2e-16       
##                                           
##                   Kappa : 0.6774          
##                                           
##  Mcnemar's Test P-Value : < 2.2e-16       
## 
## Statistics by Class:
## 
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.8968   0.6027   0.8140   0.6318   0.6981
## Specificity            0.9310   0.9373   0.9024   0.9473   0.9633
## Pos Pred Value         0.8379   0.6976   0.6379   0.7017   0.8106
## Neg Pred Value         0.9578   0.9077   0.9583   0.9292   0.9341
## Prevalence             0.2845   0.1935   0.1743   0.1639   0.1837
## Detection Rate         0.2551   0.1166   0.1419   0.1036   0.1283
## Detection Prevalence   0.3044   0.1672   0.2225   0.1476   0.1582
## Balanced Accuracy      0.9139   0.7700   0.8582   0.7896   0.8307
```

The Decision Tree model has an accuracy of **74.55%**

Build Random Forest Model

Build a Random Forest model with the Train_TrainData dataset and plot the Random Forest model

```
Model_RandomForest <- randomForest(classe ~ ., data=Train_TrainData, method="class")
Predict_RandomForest <- predict(Model_RandomForest, Test_TrainData, type = "class")
plot(Model_RandomForest, main="Random Forest Model")
```



Random Forest Model Testing

Test the Random Forest model on the Test_TrainData dataset and output the Confusion Matrix and Statistics:

```
RanForest_ConfMatrix <- confusionMatrix(Predict_RandomForest, Test_TrainData$classe)
RanForest_ConfMatrix
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1395    4    0    0    0
##          B    0  944    8    0    0
##          C    0    1  847    6    0
##          D    0    0    0  798    1
##          E    0    0    0    0  900
##
## Overall Statistics
##
##                Accuracy : 0.9959
##                  95% CI : (0.9937, 0.9975)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9948
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   0.9947   0.9906   0.9925   0.9989
## Specificity            0.9989   0.9980   0.9983   0.9998   1.0000
## Pos Pred Value         0.9971   0.9916   0.9918   0.9987   1.0000
## Neg Pred Value         1.0000   0.9987   0.9980   0.9985   0.9998
## Prevalence             0.2845   0.1935   0.1743   0.1639   0.1837
## Detection Rate         0.2845   0.1925   0.1727   0.1627   0.1835
## Detection Prevalence   0.2853   0.1941   0.1741   0.1629   0.1835
## Balanced Accuracy      0.9994   0.9964   0.9945   0.9961   0.9994
```

The Random Forest model has an accuracy of **99.59%**

4. Model Selection and Predictions

Select Model by Accuracy

The accuracy of the Random Forest model, **99.59%** is higher than the accuracy achieved with the Decision Tree model, **74.55%**, therefore the **Random Forest** model is chosen to predict 20 different test cases.

Run Model and Predict on Test Data

The Random Forest model is applied to predict results on the 20 observations found in the TestData dataset. The results are as follows:

```
FinalPredict_RandomForest <- predict(Model_RandomForest, TestData, type = "class")
FinalPredict_RandomForest
```

```
##  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
```