

Practical Machine Learning Course 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 dumbbell of 6 participants. They were asked to perform barbell lifts correctly and incorrectly in 5 different ways. These different techniques or classes are defined as:

Class A - exercise performed exactly according to the specification
Class B - exercise performed incorrectly; subject throwing the elbows to the front
Class C - exercise performed incorrectly; subject lifting the dumbbell only halfway
Class D - exercise performed incorrectly; subject lowering the dumbbell only halfway
Class E - exercise performed incorrectly; subject throwing the hips to the front

More information is available from the website <http://groupware.les.inf.puc-rio.br/har> (see the section on the Weight Lifting Exercise Dataset).

The goal of this project is to predict how well each participant performs each exercise. We will use 2 different modeling techniques - CART and Random Forest - as well as partition our data into training and testing to help increase the accuracy of model predictions.

Load required libraries

```
library(knitr)
library(caret)
```

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

```
library(rpart)
library(e1071)
library(randomForest)
```

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

Load source data

```
testing<-read.csv("C:/Users/staples/Documents/Coursera/PracticalMachineLearning/Data/pml-testing.csv")
training<-read.csv("C:/Users/staples/Documents/Coursera/PracticalMachineLearning/Data/pml-training.csv")
```

Preview source data

Let's take a quick look at the data we will be analyzing.

```
tail(training)
```

```
##           X user_name raw_timestamp_part_1 raw_timestamp_part_2
## 19617 19617   adelmo           1322832937           588324
## 19618 19618   adelmo           1322832937           588376
## 19619 19619   adelmo           1322832937           596287
## 19620 19620   adelmo           1322832937           636283
## 19621 19621   adelmo           1322832937           964299
## 19622 19622   adelmo           1322832937           972293
##           cvtd_timestamp new_window num_window roll_belt pitch_belt yaw_belt
## 19617 02/12/2011 13:35         no          864         148        -34.7        129
## 19618 02/12/2011 13:35         no          864         147        -34.8        129
## 19619 02/12/2011 13:35         no          864         145        -35.3        130
## 19620 02/12/2011 13:35         no          864         145        -35.5        130
## 19621 02/12/2011 13:35         no          864         143        -35.9        131
## 19622 02/12/2011 13:35         yes         864         143        -36.0        132
##           total_accel_belt kurtosis_roll_belt kurtosis_picth_belt
## 19617                    21
## 19618                    21
## 19619                    19
## 19620                    19
## 19621                    18
## 19622                    18          -1.175902          -1.063259
##           kurtosis_yaw_belt skewness_roll_belt skewness_roll_belt.1
## 19617
## 19618
## 19619
## 19620
## 19621
## 19622          #DIV/0!          0.196860          -0.572396
##           skewness_yaw_belt max_roll_belt max_picth_belt max_yaw_belt
## 19617                    NA                    NA
## 19618                    NA                    NA
## 19619                    NA                    NA
## 19620                    NA                    NA
## 19621                    NA                    NA
## 19622          #DIV/0!          132          25          -1.2
##           min_roll_belt min_pitch_belt min_yaw_belt amplitude_roll_belt
## 19617                    NA                    NA                    NA
## 19618                    NA                    NA                    NA
## 19619                    NA                    NA                    NA
## 19620                    NA                    NA                    NA
## 19621                    NA                    NA                    NA
## 19622          123          18          -1.2          9
##           amplitude_pitch_belt amplitude_yaw_belt var_total_accel_belt
## 19617                    NA                    NA
## 19618                    NA                    NA
## 19619                    NA                    NA
## 19620                    NA                    NA
```

##	19621	NA			NA	
##	19622	7	0.00		5.6268	
##		avg_roll_belt	stddev_roll_belt	var_roll_belt	avg_pitch_belt	
##	19617	NA	NA	NA	NA	
##	19618	NA	NA	NA	NA	
##	19619	NA	NA	NA	NA	
##	19620	NA	NA	NA	NA	
##	19621	NA	NA	NA	NA	
##	19622	151.1481	4.7532	22.5926	-33.6259	
##		stddev_pitch_belt	var_pitch_belt	avg_yaw_belt	stddev_yaw_belt	
##	19617	NA	NA	NA	NA	
##	19618	NA	NA	NA	NA	
##	19619	NA	NA	NA	NA	
##	19620	NA	NA	NA	NA	
##	19621	NA	NA	NA	NA	
##	19622	1.3952	1.9466	126.8889	2.7503	
##		var_yaw_belt	gyros_belt_x	gyros_belt_y	gyros_belt_z	accel_belt_x
##	19617	NA	0.37	0.00	-0.62	49
##	19618	NA	0.37	-0.02	-0.67	50
##	19619	NA	0.39	-0.02	-0.67	47
##	19620	NA	0.37	0.00	-0.64	47
##	19621	NA	0.37	-0.02	-0.59	46
##	19622	7.5641	0.35	-0.02	-0.57	42
##		accel_belt_y	accel_belt_z	magnet_belt_x	magnet_belt_y	magnet_belt_z
##	19617	25	-195	191	540	-415
##	19618	26	-193	190	552	-412
##	19619	15	-179	192	558	-389
##	19620	13	-177	191	560	-386
##	19621	18	-172	190	565	-370
##	19622	25	-171	194	566	-349
##		roll_arm	pitch_arm	yaw_arm	total_accel_arm	var_accel_arm
##	19617	-99.1	-33.7	79.4	48	NA
##	19618	-99.4	-33.8	79.0	47	NA
##	19619	-99.6	-34.5	77.3	45	NA
##	19620	-99.6	-35.1	76.3	44	NA
##	19621	-98.6	-36.7	73.5	41	NA
##	19622	-97.6	-37.7	71.5	41	54.2564
##		avg_roll_arm	stddev_roll_arm	var_roll_arm	avg_pitch_arm	
##	19617	NA	NA	NA	NA	
##	19618	NA	NA	NA	NA	
##	19619	NA	NA	NA	NA	
##	19620	NA	NA	NA	NA	
##	19621	NA	NA	NA	NA	
##	19622	-91.6481	9.1687	84.0649	-37.6519	
##		stddev_pitch_arm	var_pitch_arm	avg_yaw_arm	stddev_yaw_arm	
##	19617	NA	NA	NA	NA	
##	19618	NA	NA	NA	NA	
##	19619	NA	NA	NA	NA	
##	19620	NA	NA	NA	NA	
##	19621	NA	NA	NA	NA	
##	19622	3.6161	13.0764	66.3111	15.4797	
##		var_yaw_arm	gyros_arm_x	gyros_arm_y	gyros_arm_z	accel_arm_x
##	19617	NA	0.31	-0.45	0.28	67
##	19618	NA	0.55	-0.51	0.25	75

```

## 19619      NA      0.88      -0.71      0.21      52
## 19620      NA      0.98      -0.82      0.23      62
## 19621      NA      1.35      -1.00      0.49      70
## 19622    239.621      1.51      -1.06      0.59      58
##      accel_arm_y accel_arm_z magnet_arm_x magnet_arm_y magnet_arm_z
## 19617      -181      -432      268      -138      -566
## 19618      -184      -415      272      -134      -562
## 19619      -163      -406      288      -112      -559
## 19620      -167      -391      309      -103      -541
## 19621      -164      -359      339      -91      -543
## 19622      -152      -365      362      -84      -539
##      kurtosis_roll_arm kurtosis_pitch_arm kurtosis_yaw_arm
## 19617
## 19618
## 19619
## 19620
## 19621
## 19622      -1.32631      0.50959      -0.62736
##      skewness_roll_arm skewness_pitch_arm skewness_yaw_arm max_roll_arm
## 19617
## 19618
## 19619
## 19620
## 19621
## 19622      -0.51721      -1.26872      -0.77150      -33.7
##      max_pitch_arm max_yaw_arm min_roll_arm min_pitch_arm min_yaw_arm
## 19617      NA      NA      NA      NA      NA
## 19618      NA      NA      NA      NA      NA
## 19619      NA      NA      NA      NA      NA
## 19620      NA      NA      NA      NA      NA
## 19621      NA      NA      NA      NA      NA
## 19622      79.5      49      -43.5      27.5      25
##      amplitude_roll_arm amplitude_pitch_arm amplitude_yaw_arm
## 19617      NA      NA      NA
## 19618      NA      NA      NA
## 19619      NA      NA      NA
## 19620      NA      NA      NA
## 19621      NA      NA      NA
## 19622      9.8      52      24
##      roll_dumbbell pitch_dumbbell yaw_dumbbell kurtosis_roll_dumbbell
## 19617      38.60998      -22.79150      -111.6131
## 19618      36.41318      -22.86197      -113.4998
## 19619      35.15281      -22.97191      -114.5256
## 19620      30.06028      -20.99018      -120.0318
## 19621      22.86333      -21.75662      -125.2459
## 19622      20.80000      -19.70000      -128.2000      -1.1322
##      kurtosis_pitch_dumbbell kurtosis_yaw_dumbbell skewness_roll_dumbbell
## 19617
## 19618
## 19619
## 19620
## 19621
## 19622      -0.7225      #DIV/0!      0.0955
##      skewness_pitch_dumbbell skewness_yaw_dumbbell max_roll_dumbbell

```

##	19617				NA
##	19618				NA
##	19619				NA
##	19620				NA
##	19621				NA
##	19622	0.1057	#DIV/0!		-19.7
##		max_pitch_dumbbell	max_yaw_dumbbell	min_roll_dumbbell	
##	19617	NA		NA	
##	19618	NA		NA	
##	19619	NA		NA	
##	19620	NA		NA	
##	19621	NA		NA	
##	19622	-92	-1.1	-33.1	
##		min_pitch_dumbbell	min_yaw_dumbbell	amplitude_roll_dumbbell	
##	19617	NA		NA	
##	19618	NA		NA	
##	19619	NA		NA	
##	19620	NA		NA	
##	19621	NA		NA	
##	19622	-128.2	-1.1	13.41	
##		amplitude_pitch_dumbbell	amplitude_yaw_dumbbell	total_accel_dumbbell	
##	19617	NA		19	
##	19618	NA		19	
##	19619	NA		18	
##	19620	NA		19	
##	19621	NA		19	
##	19622	36.2	0.00	19	
##		var_accel_dumbbell	avg_roll_dumbbell	stddev_roll_dumbbell	
##	19617	NA	NA	NA	
##	19618	NA	NA	NA	
##	19619	NA	NA	NA	
##	19620	NA	NA	NA	
##	19621	NA	NA	NA	
##	19622	0.4217	37.3418	9.7828	
##		var_roll_dumbbell	avg_pitch_dumbbell	stddev_pitch_dumbbell	
##	19617	NA	NA	NA	
##	19618	NA	NA	NA	
##	19619	NA	NA	NA	
##	19620	NA	NA	NA	
##	19621	NA	NA	NA	
##	19622	95.7038	-26.8182	4.0098	
##		var_pitch_dumbbell	avg_yaw_dumbbell	stddev_yaw_dumbbell	
##	19617	NA	NA	NA	
##	19618	NA	NA	NA	
##	19619	NA	NA	NA	
##	19620	NA	NA	NA	
##	19621	NA	NA	NA	
##	19622	16.0788	-109.9671	9.7475	
##		var_yaw_dumbbell	gyros_dumbbell_x	gyros_dumbbell_y	gyros_dumbbell_z
##	19617	NA	0.34	-0.31	-0.51
##	19618	NA	0.32	-0.26	-0.36
##	19619	NA	0.24	-0.24	0.05
##	19620	NA	0.22	-0.27	0.21
##	19621	NA	0.13	-0.14	0.34

```

## 19622          95.0143          0.02          0.02          0.36
##      accel_dumbbell_x accel_dumbbell_y accel_dumbbell_z magnet_dumbbell_x
## 19617          -42          70          -167          -624
## 19618          -42          66          -168          -618
## 19619          -41          62          -164          -618
## 19620          -38          54          -170          -621
## 19621          -40          42          -176          -628
## 19622          -36          38          -176          -627
##      magnet_dumbbell_y magnet_dumbbell_z roll_forearm pitch_forearm
## 19617          127           8           0           0
## 19618          134           0           0           0
## 19619          116           7           0           0
## 19620          113          -9           0           0
## 19621          116           0           0           0
## 19622          119           2           0           0
##      yaw_forearm kurtosis_roll_forearm kurtosis_pitch_forearm
## 19617           0
## 19618           0
## 19619           0
## 19620           0
## 19621           0
## 19622           0          #DIV/0!          #DIV/0!
##      kurtosis_yaw_forearm skewness_roll_forearm skewness_pitch_forearm
## 19617
## 19618
## 19619
## 19620
## 19621
## 19622          #DIV/0!          #DIV/0!          #DIV/0!
##      skewness_yaw_forearm max_roll_forearm max_pitch_forearm
## 19617
## 19618
## 19619
## 19620
## 19621
## 19622          #DIV/0!           0           0
##      max_yaw_forearm min_roll_forearm min_pitch_forearm min_yaw_forearm
## 19617
## 19618
## 19619
## 19620
## 19621
## 19622          #DIV/0!           0           0          #DIV/0!
##      amplitude_roll_forearm amplitude_pitch_forearm amplitude_yaw_forearm
## 19617
## 19618
## 19619
## 19620
## 19621
## 19622           0           0          #DIV/0!
##      total_accel_forearm var_accel_forearm avg_roll_forearm
## 19617          27
## 19618          29
## 19619          29

```

##	19620	29	NA	NA	
##	19621	32	NA	NA	
##	19622	33	30.10541	0	
##		stddev_roll_forearm	var_roll_forearm	avg_pitch_forearm	
##	19617	NA	NA	NA	
##	19618	NA	NA	NA	
##	19619	NA	NA	NA	
##	19620	NA	NA	NA	
##	19621	NA	NA	NA	
##	19622	0	0	0	
##		stddev_pitch_forearm	var_pitch_forearm	avg_yaw_forearm	
##	19617	NA	NA	NA	
##	19618	NA	NA	NA	
##	19619	NA	NA	NA	
##	19620	NA	NA	NA	
##	19621	NA	NA	NA	
##	19622	0	0	0	
##		stddev_yaw_forearm	var_yaw_forearm	gyros_forearm_x	gyros_forearm_y
##	19617	NA	NA	1.75	-1.91
##	19618	NA	NA	1.73	-1.75
##	19619	NA	NA	1.59	-1.36
##	19620	NA	NA	1.54	-1.20
##	19621	NA	NA	1.48	-0.90
##	19622	0	0	1.38	-0.64
##		gyros_forearm_z	accel_forearm_x	accel_forearm_y	accel_forearm_z
##	19617	-0.38	-255	-50	-30
##	19618	-0.25	-271	-68	-37
##	19619	0.00	-271	-91	-43
##	19620	0.05	-263	-99	-45
##	19621	0.05	-270	-141	-51
##	19622	0.08	-278	-159	-52
##		magnet_forearm_x	magnet_forearm_y	magnet_forearm_z	classe
##	19617	-226	-570	27	E
##	19618	-205	-587	6	E
##	19619	-151	-635	-36	E
##	19620	-116	-654	-70	E
##	19621	-68	-678	-98	E
##	19622	-60	-686	-110	E

Cleanse source data

As seen above, a number of the data values in the source data are N/A and some are DIV/0! or blank, so let's remove those.

```
train<-read.csv("C:/Users/staples/Documents/Coursera/PracticalMachineLearning/Data/pml-training.csv",header=TRUE)
test<-read.csv("C:/Users/staples/Documents/Coursera/PracticalMachineLearning/Data/pml-testing.csv",header=TRUE)
trainNA<-apply(train,2,function(x) {sum(is.na(x))})
testNA<-apply(test,2,function(y) {sum(is.na(y))})
train<-train[,which(trainNA == 0)]
test<-test[,which(testNA == 0)]
```

After cleansing data, 60 variables remain (out of an original count of 160 variables) in both the train and test

data.

Eliminate unnecessary variables

Since we are only concerned with how well participants did the exercise (data from accelerometers from belt, forearm, arm, and dumbbell from each of the participants) and are not concerned with the names of the participants or when they did the exercises, we can remove the first 7 variables (X, user_name, raw_timestamp_part_1, raw_timestamp_part_2, cvtd_timestamp, new_window, num_window) from the train and test data.

```
train<-train[,-c(1:7)]
test<-test[,-c(1:7)]
```

The final variable in the test data set, problem_id, is not needed, so let's also remove that one.

```
test<-test[,c(1:52)]
```

And now a quick look at the variables in our source data.

```
str(train)
```

```
## 'data.frame':    19622 obs. of  53 variables:
## $ roll_belt      : num  1.41 1.41 1.42 1.48 1.48 1.45 1.42 1.42 1.43 1.45 ...
## $ pitch_belt     : num  8.07 8.07 8.07 8.05 8.07 8.06 8.09 8.13 8.16 8.17 ...
## $ yaw_belt       : num -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 ...
## $ total_accel_belt : int  3 3 3 3 3 3 3 3 3 3 ...
## $ gyros_belt_x    : num  0 0.02 0 0.02 0.02 0.02 0.02 0.02 0.02 0.03 ...
## $ gyros_belt_y    : num  0 0 0 0 0.02 0 0 0 0 0 ...
## $ gyros_belt_z    : num -0.02 -0.02 -0.02 -0.03 -0.02 -0.02 -0.02 -0.02 -0.02 0 ...
## $ accel_belt_x    : int -21 -22 -20 -22 -21 -21 -22 -22 -20 -21 ...
## $ accel_belt_y    : int  4 4 5 3 2 4 3 4 2 4 ...
## $ accel_belt_z    : int  22 22 23 21 24 21 21 21 24 22 ...
## $ magnet_belt_x   : int -3 -7 -2 -6 -6 0 -4 -2 1 -3 ...
## $ magnet_belt_y   : int  599 608 600 604 600 603 599 603 602 609 ...
## $ magnet_belt_z   : int -313 -311 -305 -310 -302 -312 -311 -313 -312 -308 ...
## $ roll_arm       : num -128 -128 -128 -128 -128 -128 -128 -128 -128 -128 ...
## $ pitch_arm      : num  22.5 22.5 22.5 22.1 22.1 22 21.9 21.8 21.7 21.6 ...
## $ yaw_arm        : num -161 -161 -161 -161 -161 -161 -161 -161 -161 -161 ...
## $ total_accel_arm : int  34 34 34 34 34 34 34 34 34 34 ...
## $ gyros_arm_x     : num  0 0.02 0.02 0.02 0 0.02 0 0.02 0.02 0.02 ...
## $ gyros_arm_y     : num  0 -0.02 -0.02 -0.03 -0.03 -0.03 -0.03 -0.02 -0.03 -0.03 ...
## $ gyros_arm_z     : num -0.02 -0.02 -0.02 0.02 0 0 0 0 -0.02 -0.02 ...
## $ accel_arm_x     : int -288 -290 -289 -289 -289 -289 -289 -289 -288 -288 ...
## $ accel_arm_y     : int  109 110 110 111 111 111 111 111 109 110 ...
## $ accel_arm_z     : int -123 -125 -126 -123 -123 -122 -125 -124 -122 -124 ...
## $ magnet_arm_x    : int -368 -369 -368 -372 -374 -369 -373 -372 -369 -376 ...
## $ magnet_arm_y    : int  337 337 344 344 337 342 336 338 341 334 ...
```



```
## $ magnet_arm_z      : int  516 513 513 512 506 513 509 510 518 516 ...
## $ roll_dumbbell     : num  13.1 13.1 12.9 13.4 13.4 ...
## $ pitch_dumbbell    : num  -70.5 -70.6 -70.3 -70.4 -70.4 ...
## $ yaw_dumbbell      : num  -84.9 -84.7 -85.1 -84.9 -84.9 ...
## $ total_accel_dumbbell: int  37 37 37 37 37 37 37 37 37 37 ...
## $ gyros_dumbbell_x  : num   0 0 0 0 0 0 0 0 0 0 ...
## $ gyros_dumbbell_y  : num  -0.02 -0.02 -0.02 -0.02 -0.02 -0.02 -0.02 -0.02 -0.02 ...
## $ gyros_dumbbell_z  : num   0 0 0 -0.02 0 0 0 0 0 0 ...
## $ accel_dumbbell_x  : int  -234 -233 -232 -232 -233 -234 -232 -234 -232 -235 ...
## $ accel_dumbbell_y  : int   47 47 46 48 48 48 47 46 47 48 ...
## $ accel_dumbbell_z  : int  -271 -269 -270 -269 -270 -269 -270 -272 -269 -270 ...
## $ magnet_dumbbell_x : int  -559 -555 -561 -552 -554 -558 -551 -555 -549 -558 ...
## $ magnet_dumbbell_y : int   293 296 298 303 292 294 295 300 292 291 ...
## $ magnet_dumbbell_z : num  -65 -64 -63 -60 -68 -66 -70 -74 -65 -69 ...
## $ roll_forearm      : num  28.4 28.3 28.3 28.1 28 27.9 27.9 27.8 27.7 27.7 ...
## $ pitch_forearm     : num  -63.9 -63.9 -63.9 -63.9 -63.9 -63.9 -63.9 -63.8 -63.8 -63.8 ...
## $ yaw_forearm       : num  -153 -153 -152 -152 -152 -152 -152 -152 -152 -152 ...
## $ total_accel_forearm: int   36 36 36 36 36 36 36 36 36 36 ...
## $ gyros_forearm_x   : num   0.03 0.02 0.03 0.02 0.02 0.02 0.02 0.02 0.02 0.03 ...
## $ gyros_forearm_y   : num   0 0 -0.02 -0.02 0 -0.02 0 -0.02 0 0 ...
## $ gyros_forearm_z   : num  -0.02 -0.02 0 0 -0.02 -0.03 -0.02 0 -0.02 -0.02 ...
## $ accel_forearm_x   : int  192 192 196 189 189 193 195 193 193 190 ...
## $ accel_forearm_y   : int  203 203 204 206 206 203 205 205 204 205 ...
## $ accel_forearm_z   : int  -215 -216 -213 -214 -214 -215 -215 -213 -214 -215 ...
## $ magnet_forearm_x  : int  -17 -18 -18 -16 -17 -9 -18 -9 -16 -22 ...
## $ magnet_forearm_y  : num   654 661 658 658 655 660 659 660 653 656 ...
## $ magnet_forearm_z  : num   476 473 469 469 473 478 470 474 476 473 ...
## $ classe            : Factor w/ 5 levels "A","B","C","D",...: 1 1 1 1 1 1 1 1 1 1 ...
```

We are left with 53 numeric and integer variables in the train data and 52 num and int variables in the test data, with the exception of the ‘classe’ (factor) variable in the train data, which is the evaluation of how well each participant performed each exercise and is the variable we want to predict.

Set seed

Setting a seed value should enable us to get identical results in subsequent runs of the code

```
set.seed(12345)
```

Partition training data into training and testing (cross validation)

We will partition our training data into trainPart and testPart, with a 75%/25% split, respectively. The testPart data will be used as validation to help ensure we don’t overfit our model to the trainPart data; that is, we will train the models with the trainPart data and then test or validate with the testPart data to help ensure the model generalizes well to data other than the testPart.

```
partition<-createDataPartition(y=train$classe,p=0.75,list=FALSE)
trainPart<-train[partition,]
testPart<-train[-partition,]
```

Exploratory Data Analysis

Let's evaluate the "classe" results from the training partition.

```
plot(trainPart$classe,main="Categories of the classe variable in the training partition",xlab="classe",
```



In our training partition, we see that class A has more than 4000 observations, significantly higher than each of the other classes, which range between about 2500 and 3000. This is good, because class A is correct technique, but the combined frequencies of classes B - E (incorrect technique) exceeds the total for class A.

Model comparisons

Let's construct a simple CART model to predict exercise results:

```
cartTrain<-rpart(classe~.,data=trainPart,method="class")
cartPredict<-predict(cartTrain,testPart,type="class")
confusionMatrix(cartPredict,testPart$classe)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##           A 1260  156   33   40   23
```

```
##           B    52  555   73   52   52
##           C    24  136  575   83   95
##           D    40   33  150  513   89
##           E    19   69   24  116  642
##
## Overall Statistics
##
##           Accuracy : 0.7229
##           95% CI : (0.7101, 0.7354)
##           No Information Rate : 0.2845
##           P-Value [Acc > NIR] : < 2.2e-16
##
##           Kappa : 0.6486
##           McNemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
##
##           Class: A Class: B Class: C Class: D Class: E
## Sensitivity      0.9032  0.5848  0.6725  0.6381  0.7125
## Specificity      0.9282  0.9421  0.9165  0.9239  0.9430
## Pos Pred Value   0.8333  0.7079  0.6298  0.6218  0.7379
## Neg Pred Value   0.9602  0.9044  0.9298  0.9287  0.9358
## Prevalence       0.2845  0.1935  0.1743  0.1639  0.1837
## Detection Rate   0.2569  0.1132  0.1173  0.1046  0.1309
## Detection Prevalence 0.3083  0.1599  0.1862  0.1682  0.1774
## Balanced Accuracy 0.9157  0.7635  0.7945  0.7810  0.8278
```

Our CART model has a prediction accuracy of 72.3% and a reasonably tight 95% confidence interval. We see that 1260 participants are correctly predicted for class A, 555 for class B, and so on. The specificity is above 0.91 for all 5 classes, but the sensitivity varies between 0.58 (class B) and 0.90 (class A).

Let's now construct a random forest model to predict exercise results:

```
rfTrain<-train(classe~.,data=trainPart,method="rf")
rfPredict<-predict(rfTrain,testPart)
confusionMatrix(rfPredict,testPart$classe)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##           A 1393     6     0     0     0
##           B     2  938     2     0     0
##           C     0     5  849    10     2
##           D     0     0     4   794     5
##           E     0     0     0     0  894
##
## Overall Statistics
##
##           Accuracy : 0.9927
##           95% CI : (0.9899, 0.9949)
##           No Information Rate : 0.2845
```

```
##      P-Value [Acc > NIR] : < 2.2e-16
##
##                      Kappa : 0.9907
## McNemar's Test P-Value : NA
##
## Statistics by Class:
##
##                Class: A Class: B Class: C Class: D Class: E
## Sensitivity          0.9986   0.9884   0.9930   0.9876   0.9922
## Specificity          0.9983   0.9990   0.9958   0.9978   1.0000
## Pos Pred Value       0.9957   0.9958   0.9804   0.9888   1.0000
## Neg Pred Value       0.9994   0.9972   0.9985   0.9976   0.9983
## Prevalence           0.2845   0.1935   0.1743   0.1639   0.1837
## Detection Rate       0.2841   0.1913   0.1731   0.1619   0.1823
## Detection Prevalence 0.2853   0.1921   0.1766   0.1637   0.1823
## Balanced Accuracy    0.9984   0.9937   0.9944   0.9927   0.9961
```

Our Random Forest model has a prediction accuracy of 99.3% and a very tight 95% confidence interval. We see that 1393 participants are correctly predicted for class A, 938 for class B, and so on, and we have very few misclassification errors. The specificity is above .995 for all 5 classes, and the sensitivity varies between .987 and .998. This is a fairly dramatic improvement over the results from our CART model, so we select the Random Forest model for our predictions.

Accuracy and out of sample error

We see above that the Random Forest algorithm performed better than our CART model. Accuracy for the Random Forest model was 0.993 (95% CI: (.9899,.9949)) compared to 0.723 for CART (95% CI: (.7101,.7354)). The accuracy of the Random Forest model suggests the expected out-of-sample error is estimated at 0.007, or 0.7%.

Predictions of 20 observations based on Random Forest model

Using the code provided in the prediction submission instructions

This will write out the predicted class results (e.g., A, B, C...) for 20 observations - each to an individual file - which will be submitted in the subsequent step of the assignment.