

Practical Machine Learning Course | Peer Review Project

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21 october 2016

Synopsis

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, our goal will be to use data from accelerometers on the belt, forearm, arm, and dumbbell of 6 participants to predict the quality (class) of exercise execution

The goal of the project is to predict the manner in which they did the exercise. This is the “classe” variable in the training set. We’ll use all of the other variables to predict the class. This report describes the model building process as well as cross validation procedures, estimation of the expected out of sample error.

The resulting model will be used to predict 20 different test cases.

The Data Description

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. More information is available from the website here:
<http://groupware.les.inf.puc-rio.br/har> (<http://groupware.les.inf.puc-rio.br/har>)

The data comes in two files: training and testing.

Executive summary & Results highlight:

Based on the analyzed statistics and models it turns out that:

- The data allows us to build very accurate model
- Out of 3 used models: Random Forest, SVM Radial and GBM, the RF model showed the best accuracy (>>99%) and was used for further predictions
- The selected model also showed very zero out-of-sample error rate when checked on testing data (even smaller, than for training data) reaching accuracy of 100%
- The RF model applied to testing data resulted in 100% correct predictions

Loading and preparing data, loading required packages

Including required packages

```
library(caret)
library(ggplot2)
library(rattle)
```

```
## Warning: Failed to load RGtk2 dynamic library, attempting to install it.
```

```
set.seed(20161021) # setting seed for reproducibility
```

Download raw data files

```
# Download data
trainUrl<-"https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
testUrl<-"https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"

trainCsv <- "pml-training.csv"
testCsv <- "pml-testing.csv"

if (!file.exists(trainCsv)) {download.file(trainUrl, destfile=trainCsv, method="curl")}
if (!file.exists(testCsv)) {download.file(testUrl, destfile=testCsv, method="curl")}

# Read files into R
train <- read.table(trainCsv, sep="," , dec=".", header = TRUE, na.strings=c("NA",""))
test <- read.table(testCsv, sep="," , dec=".", header = TRUE, na.strings=c("NA",""))

# Removing unnecessary variables
rm(testCsv, testUrl, trainCsv, trainUrl)
```

Cleaning data

In order to feed the algorithms with the correct data we'll clean up our data set

Cleaning nero zero variance predictors (NZV)

We'll use the 'nearZeroVar' from caret package to remove predictors' which variance is close to 0

```
NZV <- nearZeroVar(train, saveMetrics = TRUE)
train <- train[, !NZV$nzv]

# Let's check how many variables were dropped
sum(NZV$nzv)
```

```
## [1] 43
```

With this pricedure we've totally dropped 43 variables

Cleaning predictors which do not relate to the excercise

The first columns contains descriptive data (e.g. individual name) and are not useful to predict the exercise classe

```
train <- train[, -(1:6)]
```

Because Random Forest model doesn't work well with NA's, we'll drop all the variables, with number of NAs > 1300

```
train <- train[, colSums(is.na(train)) < 1300 ]
```

Let's check what are the dimensions of the resulting train data frame

```
dim(train)
```

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

Splitting training data set 80/20

As a next step we'll split the training data set into training (80%) and testing (20%, to check out-of-sample errors rate for our model) The method for splitting is caret's function "createDataPartition".

```
inTrain <- createDataPartition(train$classe, p=0.80, list=FALSE)
training <- train[inTrain, ]
testing <- train[-inTrain, ]
```

Model Parameters and preprocessing

We'll gather modeling options into 'trainctrl' variable via trainControl function of the caret package. The function controls the computational nuances of the train function.

- To remove noise and redundant (highly correlated variables) we'll use PCA preprocessing
- To avoid overfitting we'll use cross validation (5 times per each model)

```
trainctrl <- trainControl(method = "cv", number = 5 , preProcOptions="pca")
```

Modeling and models comparison

The full list of caret's algorithms is presented here (<https://topepo.github.io/caret/modelList.html> (<https://topepo.github.io/caret/modelList.html>)). For our purposes we'll use and compare only several of them: Random Forest (rf), Gradient Boosting Machine (GBM) and Support Vector Machine (SVM) These models are very widely used and are considered quite good

We'll use cache=TRUE Knitr option for models training to save time on rebuilds

```
rf <- train(classe ~ ., data = train, method = "rf", trControl= trainctrl)
svmr <- train(classe ~ ., data = train, method = "svmRadial", trControl= trainctrl)
gbm <- train(classe ~ ., data = train, method = "gbm", trControl= trainctrl)
```

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1244
##	2	1.5233	nan	0.1000	0.0870
##	3	1.4661	nan	0.1000	0.0681
##	4	1.4223	nan	0.1000	0.0549
##	5	1.3868	nan	0.1000	0.0513
##	6	1.3543	nan	0.1000	0.0429
##	7	1.3262	nan	0.1000	0.0359
##	8	1.3028	nan	0.1000	0.0321
##	9	1.2825	nan	0.1000	0.0315
##	10	1.2627	nan	0.1000	0.0322
##	20	1.1052	nan	0.1000	0.0184
##	40	0.9352	nan	0.1000	0.0090
##	60	0.8278	nan	0.1000	0.0065
##	80	0.7478	nan	0.1000	0.0043
##	100	0.6856	nan	0.1000	0.0036
##	120	0.6350	nan	0.1000	0.0033
##	140	0.5915	nan	0.1000	0.0023
##	150	0.5737	nan	0.1000	0.0025

##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1839
##	2	1.4893	nan	0.1000	0.1301
##	3	1.4061	nan	0.1000	0.1053
##	4	1.3385	nan	0.1000	0.0823
##	5	1.2849	nan	0.1000	0.0738
##	6	1.2376	nan	0.1000	0.0639
##	7	1.1979	nan	0.1000	0.0630
##	8	1.1588	nan	0.1000	0.0528
##	9	1.1250	nan	0.1000	0.0457
##	10	1.0965	nan	0.1000	0.0416
##	20	0.8946	nan	0.1000	0.0296
##	40	0.6775	nan	0.1000	0.0131
##	60	0.5546	nan	0.1000	0.0118
##	80	0.4674	nan	0.1000	0.0053
##	100	0.4031	nan	0.1000	0.0036
##	120	0.3498	nan	0.1000	0.0033
##	140	0.3082	nan	0.1000	0.0026
##	150	0.2905	nan	0.1000	0.0027

##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.2357
##	2	1.4585	nan	0.1000	0.1590
##	3	1.3581	nan	0.1000	0.1280
##	4	1.2776	nan	0.1000	0.1070
##	5	1.2105	nan	0.1000	0.0901
##	6	1.1545	nan	0.1000	0.0705
##	7	1.1081	nan	0.1000	0.0769
##	8	1.0606	nan	0.1000	0.0680
##	9	1.0185	nan	0.1000	0.0474
##	10	0.9884	nan	0.1000	0.0590
##	20	0.7472	nan	0.1000	0.0213
##	40	0.5248	nan	0.1000	0.0120

##	60	0.4051	nan	0.1000	0.0081
##	80	0.3277	nan	0.1000	0.0063
##	100	0.2693	nan	0.1000	0.0029
##	120	0.2265	nan	0.1000	0.0012
##	140	0.1937	nan	0.1000	0.0020
##	150	0.1778	nan	0.1000	0.0017
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1276
##	2	1.5236	nan	0.1000	0.0880
##	3	1.4655	nan	0.1000	0.0686
##	4	1.4206	nan	0.1000	0.0526
##	5	1.3858	nan	0.1000	0.0444
##	6	1.3565	nan	0.1000	0.0436
##	7	1.3284	nan	0.1000	0.0397
##	8	1.3031	nan	0.1000	0.0358
##	9	1.2805	nan	0.1000	0.0304
##	10	1.2605	nan	0.1000	0.0313
##	20	1.1082	nan	0.1000	0.0155
##	40	0.9388	nan	0.1000	0.0091
##	60	0.8328	nan	0.1000	0.0053
##	80	0.7531	nan	0.1000	0.0057
##	100	0.6889	nan	0.1000	0.0032
##	120	0.6385	nan	0.1000	0.0028
##	140	0.5955	nan	0.1000	0.0030
##	150	0.5766	nan	0.1000	0.0025
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1867
##	2	1.4894	nan	0.1000	0.1292
##	3	1.4053	nan	0.1000	0.1039
##	4	1.3394	nan	0.1000	0.0850
##	5	1.2856	nan	0.1000	0.0748
##	6	1.2384	nan	0.1000	0.0704
##	7	1.1940	nan	0.1000	0.0560
##	8	1.1579	nan	0.1000	0.0553
##	9	1.1231	nan	0.1000	0.0424
##	10	1.0966	nan	0.1000	0.0446
##	20	0.8967	nan	0.1000	0.0229
##	40	0.6869	nan	0.1000	0.0099
##	60	0.5616	nan	0.1000	0.0052
##	80	0.4750	nan	0.1000	0.0071
##	100	0.4077	nan	0.1000	0.0041
##	120	0.3575	nan	0.1000	0.0043
##	140	0.3144	nan	0.1000	0.0018
##	150	0.2980	nan	0.1000	0.0021
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.2397
##	2	1.4609	nan	0.1000	0.1612
##	3	1.3588	nan	0.1000	0.1321
##	4	1.2761	nan	0.1000	0.1053
##	5	1.2103	nan	0.1000	0.0910
##	6	1.1529	nan	0.1000	0.0732

##	7	1.1064	nan	0.1000	0.0651
##	8	1.0660	nan	0.1000	0.0577
##	9	1.0296	nan	0.1000	0.0610
##	10	0.9922	nan	0.1000	0.0602
##	20	0.7652	nan	0.1000	0.0232
##	40	0.5353	nan	0.1000	0.0151
##	60	0.4109	nan	0.1000	0.0077
##	80	0.3302	nan	0.1000	0.0060
##	100	0.2714	nan	0.1000	0.0043
##	120	0.2289	nan	0.1000	0.0029
##	140	0.1954	nan	0.1000	0.0030
##	150	0.1814	nan	0.1000	0.0018

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1258
##	2	1.5243	nan	0.1000	0.0879
##	3	1.4667	nan	0.1000	0.0643
##	4	1.4236	nan	0.1000	0.0546
##	5	1.3881	nan	0.1000	0.0524
##	6	1.3551	nan	0.1000	0.0424
##	7	1.3273	nan	0.1000	0.0351
##	8	1.3045	nan	0.1000	0.0383
##	9	1.2799	nan	0.1000	0.0325
##	10	1.2597	nan	0.1000	0.0303
##	20	1.1091	nan	0.1000	0.0189
##	40	0.9345	nan	0.1000	0.0121
##	60	0.8284	nan	0.1000	0.0073
##	80	0.7499	nan	0.1000	0.0050
##	100	0.6869	nan	0.1000	0.0039
##	120	0.6344	nan	0.1000	0.0031
##	140	0.5916	nan	0.1000	0.0024
##	150	0.5727	nan	0.1000	0.0021

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1833
##	2	1.4909	nan	0.1000	0.1287
##	3	1.4084	nan	0.1000	0.1044
##	4	1.3415	nan	0.1000	0.0816
##	5	1.2885	nan	0.1000	0.0750
##	6	1.2404	nan	0.1000	0.0706
##	7	1.1969	nan	0.1000	0.0573
##	8	1.1601	nan	0.1000	0.0527
##	9	1.1264	nan	0.1000	0.0414
##	10	1.0993	nan	0.1000	0.0459
##	20	0.8961	nan	0.1000	0.0221
##	40	0.6854	nan	0.1000	0.0126
##	60	0.5630	nan	0.1000	0.0090
##	80	0.4758	nan	0.1000	0.0044
##	100	0.4060	nan	0.1000	0.0043
##	120	0.3553	nan	0.1000	0.0030
##	140	0.3116	nan	0.1000	0.0015
##	150	0.2916	nan	0.1000	0.0026

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
----	------	---------------	---------------	----------	---------

##	1	1.6094	nan	0.1000	0.2309
##	2	1.4620	nan	0.1000	0.1604
##	3	1.3621	nan	0.1000	0.1248
##	4	1.2840	nan	0.1000	0.1043
##	5	1.2182	nan	0.1000	0.1004
##	6	1.1569	nan	0.1000	0.0819
##	7	1.1048	nan	0.1000	0.0614
##	8	1.0654	nan	0.1000	0.0608
##	9	1.0272	nan	0.1000	0.0645
##	10	0.9885	nan	0.1000	0.0521
##	20	0.7631	nan	0.1000	0.0227
##	40	0.5296	nan	0.1000	0.0128
##	60	0.4049	nan	0.1000	0.0070
##	80	0.3274	nan	0.1000	0.0034
##	100	0.2698	nan	0.1000	0.0038
##	120	0.2257	nan	0.1000	0.0020
##	140	0.1926	nan	0.1000	0.0018
##	150	0.1777	nan	0.1000	0.0020

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1278
##	2	1.5230	nan	0.1000	0.0873
##	3	1.4652	nan	0.1000	0.0674
##	4	1.4201	nan	0.1000	0.0523
##	5	1.3852	nan	0.1000	0.0522
##	6	1.3523	nan	0.1000	0.0433
##	7	1.3240	nan	0.1000	0.0350
##	8	1.3012	nan	0.1000	0.0355
##	9	1.2793	nan	0.1000	0.0351
##	10	1.2565	nan	0.1000	0.0297
##	20	1.1044	nan	0.1000	0.0163
##	40	0.9341	nan	0.1000	0.0106
##	60	0.8273	nan	0.1000	0.0054
##	80	0.7482	nan	0.1000	0.0049
##	100	0.6850	nan	0.1000	0.0037
##	120	0.6344	nan	0.1000	0.0033
##	140	0.5898	nan	0.1000	0.0013
##	150	0.5699	nan	0.1000	0.0036

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1893
##	2	1.4881	nan	0.1000	0.1287
##	3	1.4058	nan	0.1000	0.1087
##	4	1.3380	nan	0.1000	0.0821
##	5	1.2852	nan	0.1000	0.0685
##	6	1.2412	nan	0.1000	0.0742
##	7	1.1958	nan	0.1000	0.0574
##	8	1.1597	nan	0.1000	0.0526
##	9	1.1270	nan	0.1000	0.0489
##	10	1.0954	nan	0.1000	0.0441
##	20	0.8933	nan	0.1000	0.0193
##	40	0.6893	nan	0.1000	0.0131
##	60	0.5579	nan	0.1000	0.0089
##	80	0.4684	nan	0.1000	0.0053

##	100	0.4033	nan	0.1000	0.0030
##	120	0.3511	nan	0.1000	0.0027
##	140	0.3082	nan	0.1000	0.0019
##	150	0.2892	nan	0.1000	0.0030
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.2378
##	2	1.4589	nan	0.1000	0.1586
##	3	1.3573	nan	0.1000	0.1317
##	4	1.2757	nan	0.1000	0.1055
##	5	1.2100	nan	0.1000	0.0812
##	6	1.1571	nan	0.1000	0.0685
##	7	1.1133	nan	0.1000	0.0751
##	8	1.0671	nan	0.1000	0.0673
##	9	1.0260	nan	0.1000	0.0533
##	10	0.9930	nan	0.1000	0.0532
##	20	0.7649	nan	0.1000	0.0275
##	40	0.5348	nan	0.1000	0.0184
##	60	0.4059	nan	0.1000	0.0075
##	80	0.3259	nan	0.1000	0.0020
##	100	0.2686	nan	0.1000	0.0031
##	120	0.2236	nan	0.1000	0.0015
##	140	0.1907	nan	0.1000	0.0018
##	150	0.1776	nan	0.1000	0.0012
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1302
##	2	1.5223	nan	0.1000	0.0879
##	3	1.4638	nan	0.1000	0.0667
##	4	1.4203	nan	0.1000	0.0538
##	5	1.3847	nan	0.1000	0.0507
##	6	1.3520	nan	0.1000	0.0403
##	7	1.3262	nan	0.1000	0.0413
##	8	1.3007	nan	0.1000	0.0351
##	9	1.2792	nan	0.1000	0.0331
##	10	1.2568	nan	0.1000	0.0304
##	20	1.1037	nan	0.1000	0.0160
##	40	0.9366	nan	0.1000	0.0112
##	60	0.8317	nan	0.1000	0.0070
##	80	0.7502	nan	0.1000	0.0039
##	100	0.6872	nan	0.1000	0.0040
##	120	0.6370	nan	0.1000	0.0029
##	140	0.5921	nan	0.1000	0.0028
##	150	0.5734	nan	0.1000	0.0019
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1901
##	2	1.4866	nan	0.1000	0.1271
##	3	1.4048	nan	0.1000	0.1059
##	4	1.3367	nan	0.1000	0.0815
##	5	1.2841	nan	0.1000	0.0746
##	6	1.2364	nan	0.1000	0.0636
##	7	1.1955	nan	0.1000	0.0552
##	8	1.1611	nan	0.1000	0.0507

##	9	1.1294	nan	0.1000	0.0486
##	10	1.0981	nan	0.1000	0.0395
##	20	0.8949	nan	0.1000	0.0262
##	40	0.6820	nan	0.1000	0.0117
##	60	0.5594	nan	0.1000	0.0090
##	80	0.4703	nan	0.1000	0.0068
##	100	0.4051	nan	0.1000	0.0031
##	120	0.3545	nan	0.1000	0.0024
##	140	0.3142	nan	0.1000	0.0017
##	150	0.2957	nan	0.1000	0.0033
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.2336
##	2	1.4596	nan	0.1000	0.1561
##	3	1.3600	nan	0.1000	0.1255
##	4	1.2815	nan	0.1000	0.0981
##	5	1.2188	nan	0.1000	0.1024
##	6	1.1553	nan	0.1000	0.0721
##	7	1.1090	nan	0.1000	0.0655
##	8	1.0674	nan	0.1000	0.0638
##	9	1.0278	nan	0.1000	0.0653
##	10	0.9879	nan	0.1000	0.0533
##	20	0.7522	nan	0.1000	0.0252
##	40	0.5327	nan	0.1000	0.0140
##	60	0.4072	nan	0.1000	0.0099
##	80	0.3277	nan	0.1000	0.0048
##	100	0.2719	nan	0.1000	0.0030
##	120	0.2277	nan	0.1000	0.0017
##	140	0.1956	nan	0.1000	0.0017
##	150	0.1810	nan	0.1000	0.0016
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.2361
##	2	1.4597	nan	0.1000	0.1572
##	3	1.3604	nan	0.1000	0.1258
##	4	1.2805	nan	0.1000	0.1084
##	5	1.2134	nan	0.1000	0.0877
##	6	1.1594	nan	0.1000	0.0752
##	7	1.1120	nan	0.1000	0.0682
##	8	1.0697	nan	0.1000	0.0606
##	9	1.0313	nan	0.1000	0.0612
##	10	0.9941	nan	0.1000	0.0528
##	20	0.7579	nan	0.1000	0.0252
##	40	0.5369	nan	0.1000	0.0170
##	60	0.4125	nan	0.1000	0.0082
##	80	0.3320	nan	0.1000	0.0048
##	100	0.2712	nan	0.1000	0.0060
##	120	0.2274	nan	0.1000	0.0020
##	140	0.1952	nan	0.1000	0.0016
##	150	0.1818	nan	0.1000	0.0012

Let’s take a look into models accuracy results:

```
max(rf$results$Accuracy) # Random forest
```

```
## [1] 0.9946998
```

```
max(svmr$results$Accuracy) # SVM Radial
```

```
## [1] 0.9337985
```

```
max(gbm$results$Accuracy) # Gradient Boosting
```

```
## [1] 0.9619816
```

Although all models shows quite solid results (>90%), the Random Forest is true leader with 99.4% accuracy. Confusion matrix from the model summary below shows all details

```
print(rf)
```

```
## Random Forest
##
## 19622 samples
##    52 predictor
##    5 classes: 'A', 'B', 'C', 'D', 'E'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 15697, 15698, 15698, 15697, 15698
## Resampling results across tuning parameters:
##
##    mtry  Accuracy   Kappa
##    2     0.9941392  0.9925859
##    27     0.9946998  0.9932952
##    52     0.9890428  0.9861382
##
## Accuracy was used to select the optimal model using  the largest value.
## The final value used for the model was mtry = 27.
```

```
print(rf$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: 27
##
##              OOB estimate of  error rate: 0.41%
## Confusion matrix:
##      A      B      C      D      E class.error
## A 5574      5      1      0      0 0.001075269
## B   19 3773      4      1      0 0.006320780
## C    0      7 3405     10      0 0.004967855
## D    1      1   21 3189      4 0.008395522
## E    0      0    3      4 3600 0.001940671
```

We'll use this model to predict results on the testing part of the data (20% of the initial dataset) to check for out-of-sample error behavior

```
# Predicting the classes
prediction1 <- predict(rf, testing)

# Comparing classes with the actual testing dataset
confusionMatrix(prediction1, testing$classe)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction      A      B      C      D      E
##           A 1116      0      0      0      0
##           B      0  759      0      0      0
##           C      0      0  684      0      0
##           D      0      0      0  643      0
##           E      0      0      0      0  721
##
## Overall Statistics
##
##           Accuracy : 1
##           95% CI : (0.9991, 1)
##           No Information Rate : 0.2845
##           P-Value [Acc > NIR] : < 2.2e-16
##
##           Kappa : 1
##           Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##           Class: A Class: B Class: C Class: D Class: E
## Sensitivity      1.0000      1.0000      1.0000      1.0000      1.0000
## Specificity      1.0000      1.0000      1.0000      1.0000      1.0000
## Pos Pred Value    1.0000      1.0000      1.0000      1.0000      1.0000
## Neg Pred Value     1.0000      1.0000      1.0000      1.0000      1.0000
## Prevalence        0.2845      0.1935      0.1744      0.1639      0.1838
## Detection Rate     0.2845      0.1935      0.1744      0.1639      0.1838
## Detection Prevalence 0.2845      0.1935      0.1744      0.1639      0.1838
## Balanced Accuracy   1.0000      1.0000      1.0000      1.0000      1.0000
```

Accuracy on the testing data reached 100%. The out-of-sample error rate (zero) is even lower than the in-sample. That means that chances are our model is quite good.

Prediction of TEST data

We'll use our model to predict classes for test data:

```
prediction2 <- predict(rf, test)
as.data.frame(prediction2)
```

##	prediction2
## 1	B
## 2	A
## 3	B
## 4	A
## 5	A
## 6	E
## 7	D
## 8	B
## 9	A
## 10	A
## 11	B
## 12	C
## 13	B
## 14	A
## 15	E
## 16	E
## 17	A
## 18	B
## 19	B
## 20	B

The prediction seems correct, as the final score is 100% (20/20)