

Practical Machine Learning Project

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Overview:

Background

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: HAR (see the section on the Weight Lifting Exercise Dataset).

The training data for this project are available here:

<https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv>

The test data are available here:

<https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv>

```
training<-read.csv("./pml-training.csv")
testing<-read.csv("./pml-testing.csv")
```

Data Preprocessing

First of all, we give the data a first look: is there any missing values?

```
unique(sapply(training,function(i) i%>%is.na%>%sum))
```

```
## [1]      0 19216
```

So there are only two types of columns: no missing values and contains 19216 missing values.

```
table(sapply(training,function(i) i%>%is.na%>%sum))
```

```
##
##      0 19216
##    93     67
```

There are 93 columns with no missing values and 67 columns with 19216 missing values. Is there any coincidence here since those columns all have the same number of missing values? We will look at the `new_window` columns to see what happened

```
table(training$new_window)
```

```
##
##    no   yes
## 19216   406
```

We can roughly see that the number of `no` in `new_window` is equal to the observed number of missing values. And indeed by closer looking at the data, we confirm that all missing values belong to the category `new_window=="no"`.

Now have a look at the testing data with variable `new_window`

```
testing$new_window
```

```
## [1] no no no no no no no no no no no no no no no no no no no no
## Levels: no
```

They are all `no`. Technically we need to divide the data into two parts and build regression models for each part respectively. But in this project, we will only look at the subset of the data with `new_window="no"`. With this subsetted data, we can remove all the columns with missing values without losing any information.

```
new_train<-subset(training,new_window=="no")
```

However, the missing values in the data can be the values `#DIV/0!` or `" "`. We remove all the columns with missing values

```
new_train[new_train==""]<-NA;
new_train[new_train=="#DIV/0!"]<-NA;
cleanedTrain <- new_train[, colSums(is.na(new_train)) == 0]
cleanedTest <- testing[, colSums(is.na(testing)) == 0]
dim(cleanedTrain)
```

```
## [1] 19216    60
```

```
dim(cleanedTest)
```

```
## [1] 20 60
```

After cleaning the missing data, the training data and the testing data contains 60 variables. However, the variables containing the information of users, timestamp and windows don't contribute to the regression then we remove all of these variables.

```
cleanedTrain<-cleanedTrain[,-c(1:7)]
cleanedTest<-cleanedTest[,-c(1:7)]
```

Finally, the data contains 53 variables.

```
inTrain <- createDataPartition(cleanedTrain$classe, p = 0.7, list = FALSE)
train <- cleanedTrain[inTrain, ]
valid <- cleanedTrain[-inTrain, ]

x_predictor<-cleanedTest[,-53]
```

Building models

Classification Trees

```
fit_rpart <- train(classe ~ ., data = train, method = "rpart")
print(fit_rpart, digits = 4)
```

```
## CART
##
## 13453 samples
##    52 predictor
##    5 classes: 'A', 'B', 'C', 'D', 'E'
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
```

```
## Summary of sample sizes: 13453, 13453, 13453, 13453, 13453, 13453, ...
## Resampling results across tuning parameters:
##
##   cp      Accuracy  Kappa
##   0.03824 0.5019    0.35402
##   0.05965 0.3959    0.17367
##   0.11369 0.3456    0.09164
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was cp = 0.03824.
```

The accuracy of the algorithm

```
predict_rpart <- predict(fit_rpart, valid)
confusionMatrix(valid$classe, predict_rpart)$overall[1]
```

```
## Accuracy
## 0.4992192
```

The accuracy of the classification tree algorithm is too poor. We will investigate the accuracy of Random Forest

Random Forest

```
fit_rf<-train(classe ~ ., data = train, method = "rf",trControl=trainControl(method = "cv", number = 5))
print(fit_rpart, digits = 4)
```

```
## CART
##
## 13453 samples
##   52 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 13453, 13453, 13453, 13453, 13453, 13453, ...
## Resampling results across tuning parameters:
##
##   cp      Accuracy  Kappa
##   0.03824 0.5019    0.35402
##   0.05965 0.3959    0.17367
##   0.11369 0.3456    0.09164
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was cp = 0.03824.
```

The accuracy of the algorithm

```
predict_rf <- predict(fit_rf, valid)
confusionMatrix(valid$classe, predict_rf)$overall[1]
```

```
## Accuracy
## 0.9928856
```

The accuracy of Random Forest is 99.24% which is too high and is the signal of overfitting.

Generalised Boosting Model

Construct the model

```
gbm_fit<-train(classe ~ ., data = train, method = "gbm",trControl=trainControl(method = "repeatedcv", n
## 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
##
```

## Iter	TrainDeviance	ValidDeviance	StepSize	Improve
## 1	1.6094	nan	0.1000	0.1278
## 2	1.5229	nan	0.1000	0.0859
## 3	1.4643	nan	0.1000	0.0671
## 4	1.4204	nan	0.1000	0.0535
## 5	1.3848	nan	0.1000	0.0494
## 6	1.3522	nan	0.1000	0.0409
## 7	1.3258	nan	0.1000	0.0392
## 8	1.3005	nan	0.1000	0.0361
## 9	1.2777	nan	0.1000	0.0304
## 10	1.2574	nan	0.1000	0.0337
## 20	1.0980	nan	0.1000	0.0196
## 40	0.9253	nan	0.1000	0.0087
## 60	0.8193	nan	0.1000	0.0065
## 80	0.7390	nan	0.1000	0.0042
## 100	0.6767	nan	0.1000	0.0032
## 120	0.6239	nan	0.1000	0.0035
## 140	0.5796	nan	0.1000	0.0021
## 150	0.5602	nan	0.1000	0.0019
##				

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1907
##	2	1.4887	nan	0.1000	0.1291
##	3	1.4047	nan	0.1000	0.1052
##	4	1.3374	nan	0.1000	0.0832
##	5	1.2845	nan	0.1000	0.0820
##	6	1.2336	nan	0.1000	0.0533
##	7	1.1972	nan	0.1000	0.0613
##	8	1.1591	nan	0.1000	0.0527
##	9	1.1261	nan	0.1000	0.0500
##	10	1.0947	nan	0.1000	0.0409
##	20	0.8915	nan	0.1000	0.0259
##	40	0.6792	nan	0.1000	0.0131
##	60	0.5493	nan	0.1000	0.0062
##	80	0.4624	nan	0.1000	0.0041
##	100	0.3922	nan	0.1000	0.0042
##	120	0.3402	nan	0.1000	0.0034
##	140	0.2990	nan	0.1000	0.0022
##	150	0.2811	nan	0.1000	0.0024
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.2399
##	2	1.4584	nan	0.1000	0.1572
##	3	1.3581	nan	0.1000	0.1314
##	4	1.2757	nan	0.1000	0.1066
##	5	1.2086	nan	0.1000	0.0887
##	6	1.1504	nan	0.1000	0.0780
##	7	1.0986	nan	0.1000	0.0642
##	8	1.0574	nan	0.1000	0.0587
##	9	1.0197	nan	0.1000	0.0621
##	10	0.9825	nan	0.1000	0.0596
##	20	0.7447	nan	0.1000	0.0240
##	40	0.5218	nan	0.1000	0.0066
##	60	0.3976	nan	0.1000	0.0063
##	80	0.3190	nan	0.1000	0.0050
##	100	0.2620	nan	0.1000	0.0044
##	120	0.2176	nan	0.1000	0.0027
##	140	0.1846	nan	0.1000	0.0017
##	150	0.1701	nan	0.1000	0.0014
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1331
##	2	1.5214	nan	0.1000	0.0885
##	3	1.4641	nan	0.1000	0.0686
##	4	1.4204	nan	0.1000	0.0530
##	5	1.3855	nan	0.1000	0.0513
##	6	1.3524	nan	0.1000	0.0393
##	7	1.3261	nan	0.1000	0.0400
##	8	1.3012	nan	0.1000	0.0338
##	9	1.2795	nan	0.1000	0.0316
##	10	1.2592	nan	0.1000	0.0369
##	20	1.0984	nan	0.1000	0.0180
##	40	0.9262	nan	0.1000	0.0102
##	60	0.8152	nan	0.1000	0.0078

##	80	0.7360	nan	0.1000	0.0038
##	100	0.6752	nan	0.1000	0.0042
##	120	0.6212	nan	0.1000	0.0037
##	140	0.5782	nan	0.1000	0.0031
##	150	0.5588	nan	0.1000	0.0021
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1921
##	2	1.4865	nan	0.1000	0.1328
##	3	1.4001	nan	0.1000	0.1061
##	4	1.3333	nan	0.1000	0.0850
##	5	1.2777	nan	0.1000	0.0753
##	6	1.2289	nan	0.1000	0.0635
##	7	1.1877	nan	0.1000	0.0628
##	8	1.1490	nan	0.1000	0.0477
##	9	1.1167	nan	0.1000	0.0471
##	10	1.0867	nan	0.1000	0.0461
##	20	0.8874	nan	0.1000	0.0242
##	40	0.6733	nan	0.1000	0.0118
##	60	0.5515	nan	0.1000	0.0071
##	80	0.4623	nan	0.1000	0.0054
##	100	0.3951	nan	0.1000	0.0022
##	120	0.3453	nan	0.1000	0.0024
##	140	0.3046	nan	0.1000	0.0022
##	150	0.2862	nan	0.1000	0.0029
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.2417
##	2	1.4595	nan	0.1000	0.1646
##	3	1.3551	nan	0.1000	0.1271
##	4	1.2743	nan	0.1000	0.1164
##	5	1.2009	nan	0.1000	0.0849
##	6	1.1470	nan	0.1000	0.0736
##	7	1.0993	nan	0.1000	0.0775
##	8	1.0517	nan	0.1000	0.0544
##	9	1.0170	nan	0.1000	0.0639
##	10	0.9773	nan	0.1000	0.0528
##	20	0.7521	nan	0.1000	0.0205
##	40	0.5273	nan	0.1000	0.0100
##	60	0.4022	nan	0.1000	0.0084
##	80	0.3201	nan	0.1000	0.0039
##	100	0.2611	nan	0.1000	0.0037
##	120	0.2177	nan	0.1000	0.0016
##	140	0.1871	nan	0.1000	0.0024
##	150	0.1718	nan	0.1000	0.0011
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1268
##	2	1.5227	nan	0.1000	0.0884
##	3	1.4646	nan	0.1000	0.0691
##	4	1.4201	nan	0.1000	0.0532
##	5	1.3840	nan	0.1000	0.0477
##	6	1.3525	nan	0.1000	0.0447
##	7	1.3239	nan	0.1000	0.0357

##	8	1.3009	nan	0.1000	0.0351
##	9	1.2786	nan	0.1000	0.0310
##	10	1.2577	nan	0.1000	0.0290
##	20	1.1041	nan	0.1000	0.0180
##	40	0.9314	nan	0.1000	0.0089
##	60	0.8203	nan	0.1000	0.0053
##	80	0.7403	nan	0.1000	0.0056
##	100	0.6810	nan	0.1000	0.0061
##	120	0.6285	nan	0.1000	0.0037
##	140	0.5834	nan	0.1000	0.0027
##	150	0.5647	nan	0.1000	0.0023

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1897
##	2	1.4886	nan	0.1000	0.1312
##	3	1.4042	nan	0.1000	0.1036
##	4	1.3377	nan	0.1000	0.0840
##	5	1.2844	nan	0.1000	0.0723
##	6	1.2395	nan	0.1000	0.0672
##	7	1.1963	nan	0.1000	0.0532
##	8	1.1606	nan	0.1000	0.0551
##	9	1.1254	nan	0.1000	0.0466
##	10	1.0959	nan	0.1000	0.0536
##	20	0.8924	nan	0.1000	0.0210
##	40	0.6813	nan	0.1000	0.0114
##	60	0.5495	nan	0.1000	0.0098
##	80	0.4600	nan	0.1000	0.0062
##	100	0.3945	nan	0.1000	0.0032
##	120	0.3452	nan	0.1000	0.0019
##	140	0.3044	nan	0.1000	0.0023
##	150	0.2881	nan	0.1000	0.0024

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.2389
##	2	1.4572	nan	0.1000	0.1610
##	3	1.3551	nan	0.1000	0.1201
##	4	1.2774	nan	0.1000	0.1074
##	5	1.2106	nan	0.1000	0.0873
##	6	1.1551	nan	0.1000	0.0756
##	7	1.1068	nan	0.1000	0.0620
##	8	1.0671	nan	0.1000	0.0598
##	9	1.0288	nan	0.1000	0.0468
##	10	0.9981	nan	0.1000	0.0611
##	20	0.7572	nan	0.1000	0.0286
##	40	0.5283	nan	0.1000	0.0098
##	60	0.4042	nan	0.1000	0.0059
##	80	0.3217	nan	0.1000	0.0041
##	100	0.2645	nan	0.1000	0.0033
##	120	0.2217	nan	0.1000	0.0017
##	140	0.1879	nan	0.1000	0.0014
##	150	0.1726	nan	0.1000	0.0016

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1270

##	2	1.5217	nan	0.1000	0.0874
##	3	1.4625	nan	0.1000	0.0701
##	4	1.4176	nan	0.1000	0.0537
##	5	1.3827	nan	0.1000	0.0435
##	6	1.3531	nan	0.1000	0.0432
##	7	1.3248	nan	0.1000	0.0415
##	8	1.2977	nan	0.1000	0.0382
##	9	1.2742	nan	0.1000	0.0313
##	10	1.2533	nan	0.1000	0.0304
##	20	1.0922	nan	0.1000	0.0166
##	40	0.9240	nan	0.1000	0.0106
##	60	0.8150	nan	0.1000	0.0054
##	80	0.7339	nan	0.1000	0.0066
##	100	0.6716	nan	0.1000	0.0041
##	120	0.6207	nan	0.1000	0.0035
##	140	0.5795	nan	0.1000	0.0024
##	150	0.5592	nan	0.1000	0.0028
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1877
##	2	1.4889	nan	0.1000	0.1305
##	3	1.4032	nan	0.1000	0.1075
##	4	1.3342	nan	0.1000	0.0795
##	5	1.2814	nan	0.1000	0.0746
##	6	1.2339	nan	0.1000	0.0658
##	7	1.1926	nan	0.1000	0.0689
##	8	1.1504	nan	0.1000	0.0499
##	9	1.1175	nan	0.1000	0.0442
##	10	1.0900	nan	0.1000	0.0465
##	20	0.8807	nan	0.1000	0.0207
##	40	0.6772	nan	0.1000	0.0139
##	60	0.5447	nan	0.1000	0.0067
##	80	0.4581	nan	0.1000	0.0045
##	100	0.3933	nan	0.1000	0.0037
##	120	0.3405	nan	0.1000	0.0030
##	140	0.2990	nan	0.1000	0.0014
##	150	0.2824	nan	0.1000	0.0012
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.2437
##	2	1.4579	nan	0.1000	0.1658
##	3	1.3514	nan	0.1000	0.1298
##	4	1.2704	nan	0.1000	0.1099
##	5	1.2001	nan	0.1000	0.0878
##	6	1.1452	nan	0.1000	0.0672
##	7	1.1019	nan	0.1000	0.0677
##	8	1.0586	nan	0.1000	0.0680
##	9	1.0153	nan	0.1000	0.0587
##	10	0.9780	nan	0.1000	0.0499
##	20	0.7531	nan	0.1000	0.0255
##	40	0.5188	nan	0.1000	0.0131
##	60	0.3993	nan	0.1000	0.0097
##	80	0.3183	nan	0.1000	0.0056
##	100	0.2595	nan	0.1000	0.0015

##	120	0.2204	nan	0.1000	0.0018
##	140	0.1879	nan	0.1000	0.0017
##	150	0.1737	nan	0.1000	0.0016
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1289
##	2	1.5245	nan	0.1000	0.0866
##	3	1.4676	nan	0.1000	0.0657
##	4	1.4234	nan	0.1000	0.0528
##	5	1.3883	nan	0.1000	0.0523
##	6	1.3540	nan	0.1000	0.0365
##	7	1.3298	nan	0.1000	0.0384
##	8	1.3044	nan	0.1000	0.0386
##	9	1.2796	nan	0.1000	0.0285
##	10	1.2606	nan	0.1000	0.0322
##	20	1.1066	nan	0.1000	0.0173
##	40	0.9326	nan	0.1000	0.0085
##	60	0.8266	nan	0.1000	0.0067
##	80	0.7446	nan	0.1000	0.0044
##	100	0.6827	nan	0.1000	0.0038
##	120	0.6329	nan	0.1000	0.0039
##	140	0.5882	nan	0.1000	0.0022
##	150	0.5673	nan	0.1000	0.0023
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1800
##	2	1.4898	nan	0.1000	0.1300
##	3	1.4057	nan	0.1000	0.1020
##	4	1.3406	nan	0.1000	0.0846
##	5	1.2863	nan	0.1000	0.0737
##	6	1.2392	nan	0.1000	0.0709
##	7	1.1955	nan	0.1000	0.0667
##	8	1.1541	nan	0.1000	0.0510
##	9	1.1217	nan	0.1000	0.0412
##	10	1.0943	nan	0.1000	0.0443
##	20	0.8964	nan	0.1000	0.0193
##	40	0.6804	nan	0.1000	0.0144
##	60	0.5510	nan	0.1000	0.0059
##	80	0.4639	nan	0.1000	0.0069
##	100	0.3979	nan	0.1000	0.0052
##	120	0.3486	nan	0.1000	0.0034
##	140	0.3055	nan	0.1000	0.0026
##	150	0.2882	nan	0.1000	0.0010
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.2330
##	2	1.4641	nan	0.1000	0.1676
##	3	1.3603	nan	0.1000	0.1308
##	4	1.2796	nan	0.1000	0.0993
##	5	1.2169	nan	0.1000	0.0862
##	6	1.1615	nan	0.1000	0.0880
##	7	1.1078	nan	0.1000	0.0725
##	8	1.0629	nan	0.1000	0.0605
##	9	1.0243	nan	0.1000	0.0605

```
##      10      0.9862      nan      0.1000      0.0470
##      20      0.7544      nan      0.1000      0.0295
##      40      0.5283      nan      0.1000      0.0096
##      60      0.4074      nan      0.1000      0.0058
##      80      0.3248      nan      0.1000      0.0057
##     100      0.2626      nan      0.1000      0.0028
##     120      0.2207      nan      0.1000      0.0027
##     140      0.1865      nan      0.1000      0.0015
##     150      0.1729      nan      0.1000      0.0014
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.6094      nan      0.1000      0.2416
##      2      1.4591      nan      0.1000      0.1622
##      3      1.3542      nan      0.1000      0.1310
##      4      1.2720      nan      0.1000      0.1032
##      5      1.2077      nan      0.1000      0.0896
##      6      1.1522      nan      0.1000      0.0718
##      7      1.1074      nan      0.1000      0.0620
##      8      1.0674      nan      0.1000      0.0505
##      9      1.0337      nan      0.1000      0.0712
##     10      0.9900      nan      0.1000      0.0506
##     20      0.7598      nan      0.1000      0.0231
##     40      0.5309      nan      0.1000      0.0100
##     60      0.4057      nan      0.1000      0.0077
##     80      0.3232      nan      0.1000      0.0036
##    100      0.2655      nan      0.1000      0.0030
##    120      0.2233      nan      0.1000      0.0017
##    140      0.1886      nan      0.1000      0.0018
##    150      0.1753      nan      0.1000      0.0020
```

The accuracy of the algorithm

```
predict_gbm <- predict(gbm_fit, valid)
confusionMatrix(valid$classe, predict_gbm)$overall[1]
```

```
## Accuracy
## 0.9562728
```

So we have built three models one with very poor accuracy and one with a sign of overfitting. We decide to use that last one Generalised Boosting Model for the prediction

```
pred<-predict(gbm_fit,x_predictor)
pred
```

```
## [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
```