The Weight Lifting: Are you doing your unilateral dumbbell biceps curl wrong?

Machine Learning: An Inference and Prediction Analysis

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Overview

- **Background**: Data from belt, forearm, arm, and dumbbell accelerometers of 6 participants who performed dumbbell unilateral biceps curls.
- **Objectives**: Design and analysis of a machine learning model to predict unilateral dumbbell biceps.
- **Methods**: An inference and prediction analysis in R.
- **Results**: 1. The random forest model accuracy: 0.9584. 2. Predictions on pml_testing data (out-of-sample error in a new dataset): (B A A A A E D B A A A C B A E E A B B B), Levels: A B C D E). 19 0f 20 predictions were correct.
- **Conclusions**: 95% of the predictions were correct on the pml_testing dataset with the designed random forest model. The accuracy of the random forest is good. It showed high performance in predicting execution quality.

Github link

Data processing

This project involves exploring the dataset that come from the project "Wearable Computing: Accelerometers' Data Classification of Body Postures and Movements" by Ugulino, W.; Cardador, D.; Vega, K.; Velloso, E.; Milidiu, R.; Fuks, H.. Human Activity Recognition

The training and testing data for this project are available here:

The training data

The testing data

It should be predicted the manner in which the 6 participants who performed dumbbell unilateral biceps curls did the exercise. This is the "classe" variable in the training set. They were asked to perform barbell lifts correctly and incorrectly in 5 different ways.

An exploratory statistical analysis. Summary of the data.

Loading the training and test sets and displaying the internal structure.

This will allow establishing a strategy for answering the study question: The Weight Lifting - Are you doing your unilateral dumbbell biceps curl wrong?

```
## [1] "pml_training dimension: 19622 X 160"
## [1] "pml_testing dimension: 20 X 160"
## [1] "The code is available in the appendix."
```

Data cleansing

Handling Missing Values, na.strings=c("NA","#DIV/0!", ""):

The total number of rows is 19622 in pml_training. The total sum of NAs in each of the eliminated columns is greater than 19200, representing at least 97.84% of missing values in each of them. The total number of rows is 20 in pml_testing. The total sum of NAs in each of the eliminated columns is 20, representing 100% of missing values in each of them.This allows removing 100 columns from our datasets.

```
## [1] "pml_training dimension: 19622 X 60"
## [1] "pml_testing dimension: 20 X 60"
## [1] "The code is available in the appendix."
```

Handling Near Zero Variance, participant idetification and timestamps variables:

In pml_training all zeroVar results were FALSE except for the variable new_window. This variable will be removed. The variables raw_timestamp_part_1, raw_timestamp_part_2, cvtd_timestamp, num_window will be removed because they are used in a more specific type of prediction problem where data are dependent over time. The variables X and user_name will be removed too, in our case we seek to predict whether the weightlifting has been done correctly or not. This allows removing 7 columns from our datasets.

```
##            freqRatio percentUnique zeroVar  nzv
## new_window  47.33005    0.01019264   FALSE TRUE
## [1] "pml_training dimension: 19622 X 53"
## [1] "pml_testing dimension: 20 X 53"
## [1] "The code is available in the appendix."
```

An inference and prediction analysis

1. Find the right data and define your error rate

After the data cleansing, pml_training and pml_testing are going to be used.

2. Split data into: training,testing and Validation (Optional)

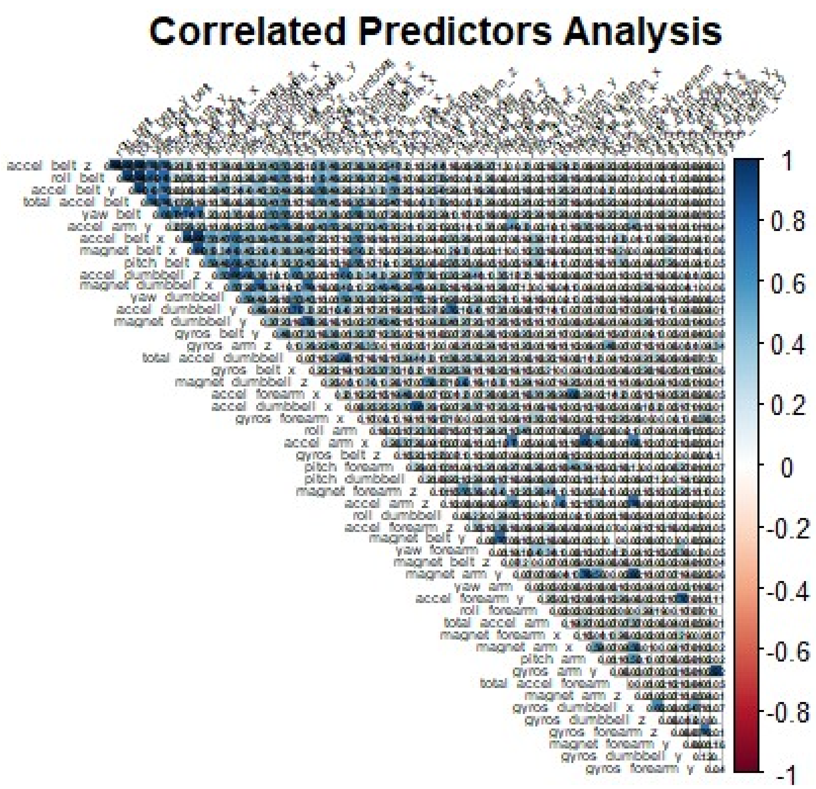
pml_training is a medium sample size. Validation is not going to be used.

```
## [1] "training dimension: 14718 X 53"
## [1] "testing dimension: 4904 X 53"
## [1] "The code is available in the appendix."
```

3. On the training set pick features, pick prediction functions and cross-validate.

Quantitatives variables highly correlated (>0.8) with each other are not useful to include them all in our model. Processing covariants witn PCA-SVD can help to reduce predictors. Cross validation must be used in the model construction .The expected out-of-sample error should be reported.

Then "Random forest, rf" is chosen. It has top performance along with boosting. Preprocessing with PCA and 5-fold Cross validation are going to be applied. The code is available in the appendix.



Preprocessing with PCA

pcaComp = 12 and thresh=0.8 was set.

```
##        PC1      PC2       PC3       PC4       PC5       PC6      PC7       PC8
## 1 3.908226 2.485103 -2.739082 0.5686560 -2.460519 0.6122135 2.450163 -1.103544
## 2 3.946956 2.501160 -2.741998 0.6292778 -2.543950 0.6474817 2.407966 -1.070013
## 3 3.912076 2.514701 -2.738037 0.5706382 -2.466756 0.6386818 2.433794 -1.081120
## 4 3.930074 2.509716 -2.730299 0.5883228 -2.500087 0.6474432 2.402445 -1.080673
## 5 3.904317 2.561618 -2.696388 0.5929345 -2.552038 0.6551338 2.390499 -1.101068
## 6 3.918251 2.534554 -2.738182 0.5795424 -2.496239 0.6401327 2.421848 -1.106315
##          PC9       PC10      PC11      PC12 classe
## 1 -0.15647675 -0.6472241 0.6042003 0.6197099      A
## 2 -0.11607012 -0.6473442 0.6020882 0.5535222      A
## 3 -0.11954061 -0.6489572 0.6028504 0.5758637      A
## 4 -0.08806033 -0.6265173 0.6210311 0.5696468      A
## 5 -0.14077346 -0.6499853 0.5920365 0.5005044      A
## 6 -0.12043119 -0.6580056 0.5869252 0.5988386      A
## [1] "The code is available in the appendix."
```

The Random Forest Model

Preprocessing with PCA was doing previously. 5-fold Cross validation was set.

```
## Random Forest
##
## 14718 samples
##    12 predictor
##     5 classes: 'A', 'B', 'C', 'D', 'E'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 11773, 11775, 11774, 11776, 11774
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa
##    2    0.9551575  0.9432688
##    7    0.9482269  0.9345018
##   12    0.9415690  0.9260773
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 2.
## [1] "The code is available in the appendix."
```

4. If no validation – apply 1x to test set

Remember that the pm_training set was partitioned. 75% to train the "rf" model (training) and 25% to evaluate it (testing). pml_testing has not been touched up to this point.

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1360   11   16    7    1
##          B   13  907   26    0    3
##          C   12    9  821    8    5
##          D   11    4   51  734    4
##          E    4    5    8    7  877
##
## Overall Statistics
##
##                Accuracy : 0.9582
##                  95% CI : (0.9522, 0.9636)
##     No Information Rate : 0.2855
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9471
##
##  Mcnemar's Test P-Value : 4.016e-07
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9714   0.9690   0.8905   0.9709   0.9854
## Specificity            0.9900   0.9894   0.9915   0.9831   0.9940
## Pos Pred Value         0.9749   0.9557   0.9602   0.9129   0.9734
## Neg Pred Value         0.9886   0.9927   0.9751   0.9946   0.9968
## Prevalence             0.2855   0.1909   0.1880   0.1542   0.1815
## Detection Rate         0.2773   0.1850   0.1674   0.1497   0.1788
## Detection Prevalence   0.2845   0.1935   0.1743   0.1639   0.1837
## Balanced Accuracy      0.9807   0.9792   0.9410   0.9770   0.9897
## [1] "The code is available in the appendix."
```

Observations: Accuracy obtained: 0.9584

My prediction model predicting 20 different test cases, pml_testing set.

what you think the expected out of sample error is?
The expected out-of-sample error is greater than the in-sample error due to noise from a new dataset.

```
##  [1] B A B A A E D B A A A C B A E E A B B B
## Levels: A B C D E
## [1] "The code is available in the appendix."
```

Conclusions

95% of the predictions were correct(19 of 20) on the pml_testing dataset with the designed random forest model. The accuracy of the random forest is good. It showed high performance in predicting execution quality.

Appendix - Code

Data processing

```
#libraries
library(dplyr)  # for manipulating, gruoping and chaining data
library(tidyr)  # for tidying data
library(plyr)   # for manipulating data
library(data.table) #  for manipulating data
library(ggplot2) ## plots
library(gridExtra) ## plots
library(caret) ## machine learning methods
library(rattle) ## decision tree and ramdom forest models, prettier plots
library(rpart) ## classification and regression trees
library(corrplot) ## plot correlation matrix
```

An exploratory statistical analysis. Summary of the data.
Loading the training and test sets and displaying the internal structure.

```
## Downloading data
if(!file.exists("./data")){dir.create("./data")}
fileUrl <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
fileUrl2 <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"
download.file(fileUrl, destfile = "./data/pml-training.csv")  # Windows OS (method="curl" not requ
ired)
download.file(fileUrl2, destfile = "./data/pml-testing.csv")
## Reading files.
pml_training <- read.csv("./data/pml-training.csv", sep=",", header =TRUE, na.strings=c("NA","#DIV
/0!", ""))
pml_testing <- read.csv("./data/pml-testing.csv", sep=",", header = TRUE, na.strings=c("NA","#DIV/
0!", ""))
## Database dimensions.
print(paste("pml_training dimension:", dim(pml_training)[1], "X",dim(pml_training)[2]))
print(paste("pml_testing dimension:", dim(pml_testing)[1], "X",dim(pml_testing)[2]))
print("The code is available in the appendix.")
```

Data cleansing
Handling Missing Values, na.strings=c("NA","#DIV/0!", ""):

```
## Data Cleansing: Handling Missing and Empty Values.
pml_training <- pml_training[,colSums(is.na(pml_training))==0 ]
pml_testing <- pml_testing[,colSums(is.na(pml_testing))==0 ]
print(paste("pml_training dimension:", dim(pml_training)[1], "X",dim(pml_training)[2]))
print(paste("pml_testing dimension:", dim(pml_testing)[1], "X",dim(pml_testing)[2]))
print("The code is available in the appendix.")
##check <- data.frame(names(pml_training_reduction),names(pml_testing_reduction))
##check
```

Handling Near Zero Variance, participant idetification and timestamps variables:

```
## In pml_training_reduction all the zeroVar results were FALSE except for the variable new_window
.
check2 <- nearZeroVar(pml_training, saveMetrics = TRUE)
check2[6,]
## Removing participant idetification and  timestamps variables
```

```
pml_training <- pml_training[,-c(1:7)]
pml_testing<- pml_testing[,-c(1:7)]
print(paste("pml_training dimension:", dim(pml_training)[1], "X",dim(pml_training)[2]))
print(paste("pml_testing dimension:", dim(pml_testing)[1], "X",dim(pml_testing)[2]))
print("The code is available in the appendix.")
remove(check2)
```

An inference and prediction analysis

1. Find the right data and define your error rate

After the data cleansing, pml_training and pml_testing are going to be used.

2. Split data into: training,testing and Validation (Optional)

```
## pml_training is a medium sample size. Validation is not going to be used.
set.seed(8888)
inTrain <- createDataPartition(y=pml_training$classe, p=0.75, list=FALSE)
training <- pml_training[inTrain,]
testing <- pml_training[-inTrain,]
print(paste("training dimension:", dim(training)[1], "X",dim(training)[2]))
print(paste("testing dimension:", dim(testing)[1], "X",dim(testing)[2]))
print("The code is available in the appendix.")
remove(pml_training)
```

3. On the training set pick features, pick prediction functions and cross-validate.

```
## Correlated predictors analysis: Quantitatives variables highly correlated (>0.8) with each othe
r are not useful to include them all in our model.
m <- abs(cor(training[,-53][sapply(training[,-53], is.numeric)]))
diag(m) <- 0
corrplot(m, order="FPC", method="square", tl.cex=0.45, tl.col="black", number.cex=0.3, diag=F, typ
e = "upper", tl.srt = 45, addshade = "all", shade.col = NA, addCoef.col = "black", title = "Correl
ated Predictors Analysis", mar=c(0,0,1,0))
```

Preprocessing with PCA

```
## Preprocessing with PCA
#training <- sapply(training, is.numeric)
preProc <- preProcess(training[,-53], method="pca", pcaComp = 12, thresh=0.8)
trainPC <- predict(preProc, training[,-53])
trainPC$classe <- training$classe
remove(m)
head(trainPC)
print("The code is available in the appendix.")
```

The Random Forest Model

```
## ModelFit_rf <- train(classe~., method="rf", prox=TRUE, preProcess="pca", trControl=trainControl
(method = "cv", number=5, allowParallel = TRUE),data=training) ## Error : cannot allocate vector o
f size 1.0 Gb ## <- I reduced the predictors before building the model. Apply PCA, previously.
ModelFit_rf <- train(classe~., method="rf", data=trainPC, trControl=trainControl(method = "cv",5),
ntree = 250, allowParallel = TRUE)
ModelFit_rf
print("The code is available in the appendix.")
```

4. If no validation – apply 1x to test set

```
testPC <- predict(preProc, testing[,-53])
testPC$classe <- testing$classe
confusionMatrix(factor(testing$classe), predict(ModelFit_rf,testPC))
print("The code is available in the appendix.")
```

My prediction model predicting 20 different test cases, pml_testing set.

```
testPC2 <- predict(preProc, pml_testing[,-53])
testPC2$problem_id <- pml_testing$problem_id
predict(ModelFit_rf,testPC2)
print("The code is available in the appendix.")
```

End/final