Machine Learning - Course Project

Aline Riquetti

1 de outubro de 2017

How you the model was built

The model was built with the intention of predict in which class an observation fits. The class is a factor variable named as "classe" and represent the answer of participants in a experiment where participants were asked to perform one set of 10 repetitions of the Unilateral Dumbbell Biceps Curl in 5 different fashions:

- exactly according to the specification (Class A)
- throwing the elbows to the front (Class B)
- lifting the dumbbell only halfway (Class C)
- lowering the dumbbell only halfway (Class D)
- throwing the hips to the front (Class E)

To predict which class an observation belongs to the other variables provided were used, as appropriate, applying some transformations in the data, if necessary.

Finally, 6 prediction algorithms were built, and from these, a last model was obtained based on the predictions obtained from the previously adjusted models;

How you the cross validation was used

Cross-validation was performed by sampling our training data set randomly without replacement into 2 subsamples:

- -Training data (70% of the original Training data set)
- -Testing data (30% of the original Training data set)
- -Validation data (20 observation of of the original Testing data set)

Our models will be fitted on the Training data set, and tested on the Testing data. Once the combined predictors model was built, he was used to predict the original Testing dataset, now called validation dataset

Expected out-of-sample error

The expected out-of-sample error corresponded to the Accuracy in the cross-validation data.

Accuracy is the proportion of correct classified observation over the total sample in the Testing data set.

The choises made

To better fit the models some transformation are necessary in the original data.

Drop the variable with to many missing

Drop identifier variables

Drop variable with low variability

Transform variables highly correlated in two principal components

Finaly, the models were built. To obtain the best model, that is, with greater accuracy, 7 models was built. 6 of the using different algorithms, and the last model, using the prediction to finally adjust the final result.

Results:

library (caret)

Load the necessaries packages

Loading required package: lattice

Loading required package: ggplot2

```
library (gridExtra)
 library(rpart)
 library (rattle)
 ## Rattle: A free graphical interface for data science with R.
 ## Version 5.1.0 Copyright (c) 2006-2017 Togaware Pty Ltd.
 ## Type 'rattle()' to shake, rattle, and roll your data.
 library (e1071)
 library(klaR)
 ## Loading required package: MASS
 library(randomForest)
 ## randomForest 4.6-12
 ## Type rfNews() to see new features/changes/bug fixes.
 ## Attaching package: 'randomForest'
 ## The following object is masked from 'package:rattle':
 ##
 ##
        importance
 ## The following object is masked from 'package:gridExtra':
 ##
 ##
        combine
 ## The following object is masked from 'package:ggplot2':
 ##
        margin
Download the data
```

```
urlTrain <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
urlTest <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"

download.file(urlTrain, destfile = "pml-training.csv")
download.file(urlTest, destfile = "pml-testing.csv")</pre>
```

Read the data and make the study reproducible

The testing data will be user as validation data since the model build need a sample to test how accurately a predictive model is

```
training_testing <- read.csv("pml-training.csv", na.strings=c("NA","#DIV/0!",""))
validation <- read.csv("pml-testing.csv", na.strings=c("NA","#DIV/0!",""))
set.seed(1235)</pre>
```

Partitioning the sample of data in training and testing

```
inTrain <- createDataPartition(y=training_testing$classe, p=0.7, list=FALSE)
training <-training_testing[inTrain, ]
testing <- training_testing[-inTrain, ]
str(training)</pre>
```

```
## $ kurtosis_yaw_belt : logi NA NA NA NA NA NA NA
## $ skewness_roll_belt : num NA NA NA NA NA NA NA NA
##
##
```

```
## $ roll_dumbbell
               : num 13.1 13.1 12.9 13.4 13.4 ...
## $ pitch_dumbbell
## $ yaw_dumbbell
               : num -70.5 -70.6 -70.3 -70.4 -70.4 ...
               : num -84.9 -84.7 -85.1 -84.9 -84.9 ...
##
##
  $ skewness_pitch_dumbbell : num NA ...
##
##
  $ skewness_yaw_dumbbell : logi NA NA NA NA NA NA ...
## $ max_roll_dumbbell
                : num NA NA NA NA NA NA NA NA NA ...
## $ max_picth_dumbbell
## $ max_yaw_dumbbell
## $ min_roll_dumbbell
                : num NA NA NA NA NA NA NA NA NA ...
               : num NA ...
               : num NA NA NA NA NA NA NA NA NA ...
##
  [list output truncated]
```

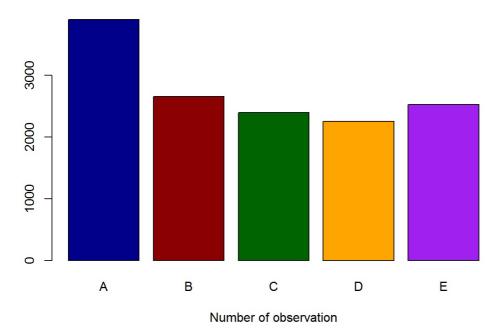
```
dim(training); dim(testing)
```

```
## [1] 13737 160
## [1] 5885 160
```

Explore Target variable

```
counts <- table(training$classe)
barplot(counts, main="Training Data - Classe distribution", xlab="Number of observation",
col=c("darkblue","darkred","darkgreen", "orange", "purple"))</pre>
```

Training Data - Classe distribution



Cleaning the data

It's possible to see the data has a lot os missing values. Some variables can't be used because the proportion of missing values is too hight.

Lets keep only the variables that have missing proportion less than 30%

```
prop_missing<-sapply(training, function(x) sum(is.na(x))/nrow(training))
var_no_missing = data.frame(var=which(prop_missing<0.3, arr.ind=T))
training2 <- training[, var_no_missing$var]
dim(training2)</pre>
```

[1] 13737 60

Eliminate no variability. Lets drop variable with no variability as well as the identification variables.

```
nearzero <- nearZeroVar(training2, saveMetrics = TRUE)
nearzero</pre>
```

```
##
                                                                                                freqRatio percentUnique zeroVar
## raw_timestamp_part_1 1.035714 6.09303341 FALSE FALSE
## raw_timestamp_part_2 1.000000 89.34265123 FALSE FALSE
## cvtd_timestamp 1.016023 0.14559220 FALSE FALSE
## new_window 48.592058 0.01455922 FALSE TRUE
## num_window 1.000000 6.23862561 FALSE FALSE
## roll_belt 1.064725 8.07308728 FALSE FALSE
## pitch_belt 1.014599 12.26614253 FALSE FALSE
## gyaw_belt 1.071225 12.99410352 FALSE FALSE
## gyros_belt_x 1.074737 0.21110868 FALSE FALSE
## gyros_belt_x 1.075758 0.98274732 FALSE FALSE
## gyros_belt_z 1.061355 1.20113552 FALSE FALSE
## accel_belt_x 1.049270 1.15745796 FALSE FALSE
## accel_belt_x 1.049270 1.15745796 FALSE FALSE
## magnet_belt_x 1.023810 2.26395865 FALSE FALSE
## magnet_belt_x 1.023810 2.26395865 FALSE FALSE
## magnet_belt_x 1.023810 2.26395865 FALSE FALSE
## magnet_belt_x 1.052308 3.14479144 FALSE FALSE
## pitch_arm 90.269231 20.12812113 FALSE FALSE
## pyaw_arm 33.056338 19.24000874 FALSE FALSE
## gyros_arm_x 1.045977 4.59343379 FALSE FALSE
## gyros_arm_x 1.045977 4.59343379 FALSE FALSE
## gyros_arm_x 1.461318 2.67889641 FALSE FALSE
## gyros_arm_x 1.000000 5.56890151 FALSE FALSE
## gyros_arm_x 1.12903 9.64548300 FALSE FALSE
## accel_arm_x 1.000000 3.82907476 FALSE FALSE
## accel_arm_x 1.100000 3.82907476 FALSE FALSE
## accel_arm_x 1.100000 7.5222385 FALSE FALSE
## accel_arm_x 1.12903 9.64548300 FALSE FALSE
## magnet_arm_x 1.00000 5.5222385 FALSE FALSE
## magnet_arm_x 1.00000 5.5222385 FALSE FALSE
## magnet_arm_x 1.12903 9.64548300 FALSE FALSE
## magnet_arm_x 1.12903 9.64548300 FALSE FALSE
## magnet_arm_x 1.00000 5.5222385 FALSE FALSE
## pitch_dumbbell 1.147727 86.94038000 FALSE FALSE
## pitch_dumbbell 1.147727 86.92697823 FALSE FALSE
## pitch_dumbbell 1.147727 86.92697823 FALSE FALSE
## pitch_dumbbell 1.147727 86.92697823 FALSE FALSE
## pitch_dumbbell 1.10797 0.31302322 FALSE FALSE
## gyros_dumbbell 1.10797 0.313
                                                                                                                                               6.09303341 FALSE FALSE
    ## raw_timestamp_part_1 1.035714
    ## raw_timestamp_part_2 1.000000 89.34265123 FALSE FALSE
    ## total_accel_dumbbell 1.107937 0.31302322 FALSE FALSE
  ## magnet_dumbbell_y 1.342105
## magnet_dumbbell_z 1.196721
                                                                                                                                               5.97655966
                                                                                                                                                                                                          FALSE FALSE
   ## magnet_dumbbell_z 1.196721 4.80454248 FALSE FALSE
## roll_forearm 11.535565 13.88221591 FALSE FALSE
## pitch_forearm 70.692308 18.86146903 FALSE FALSE
## yaw_forearm 15.930636 12.85579093 FALSE FALSE
    ## gyros_forearm_y 1.101961 5.24131907 FALSE FALSE
## gyros_forearm_z 1.178886 2.10380724 FALSE FALSE
## accel_forearm_x 1.029851 5.64169761 FALSE FALSE
## accel_forearm_y 1.073529 7.13401762 FALSE FALSE
## accel_forearm_z 1.025424 4.07658150 FALSE FALSE
## magnet_forearm_x 1.000000 10.61367111 FALSE FALSE
## magnet_forearm_y 1.216667 13.34352479 FALSE FALSE
## magnet_forearm_z 1.023810 11.74201063 FALSE FALSE
## classe 1.469526 0.03639805 FALSE FALSE
                                                                                                  1.469526 0.03639805 FALSE FALSE
```

```
## ## no yes
## 13460 277
```

```
training2 <- training2[,-6]
training2 <- training2[, -c(1:5)]
dim(training2)</pre>
```

```
## [1] 13737 54
```

Convert variable integer to numerics

```
nums <- sapply(training2, is.integer)
integer = data.frame(integ=which(nums==TRUE))
training2[integer$integ] <- lapply(training2[integer$integ], as.numeric)
str(training2); dim(training2)</pre>
```

```
## 'data.frame': 13737 obs. of 54 variables:
                  : num 11 11 11 12 12 12 12 12 12 12 ...
: num 1.41 1.41 1.42 1.48 1.48 1.43 1.45 1.43 1.42 1.45 ...
## $ num window
## $ roll_belt
## $ pitch_belt
## $ yaw_belt
                     : num 8.07 8.07 8.07 8.05 8.07 8.16 8.17 8.18 8.2 8.2 ...
                     : num -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 ...
## $ total accel belt : num 3 3 3 3 3 3 3 3 3 ...
: num 0 0 0 0 0.02 0 0 0 0 ...
## $ gyros_belt_y
                   : num 0 -0.02 -0.02 -0.03 -0.03 -0.03 -0.03 -0.03 -0.02 0 ...
## $ gyros_arm_y
                     : num -0.02 -0.02 -0.02 0.02 0 -0.02 -0.02 0 -0.02 -0.03 ...
## $ gyros arm z
                     : num -288 -290 -289 -289 -289 -288 -288 -288 -287 -289 ...
## $ accel_arm_x
## $ accel_arm_y
                     : num -123 -125 -126 -123 -123 -122 -124 -123 -124 -124 ...
## $ accel arm z
## $ magnet_arm_x
## $ magnet_arm_y
## $ magnet_arm_z
## $ roll_dumbbell
                      : num -368 -369 -368 -372 -374 -369 -376 -363 -372 -374 ...
                      : num 337 337 344 344 337 341 334 343 338 342 ...
                      : num 516 513 513 512 506 518 516 520 509 510 ...
                      : 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: num 37 37 37 37 37 37 37 37 37 37 ...
## $ gyros dumbbell x : num 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 -0.02 ...
## $ gyros_dumbbell_z : num 0 0 0 -0.02 0 0 0 0 -0.02 0 ...
\#\# $ accel dumbbell x : num -234 -233 -232 -232 -233 -232 -235 -233 -234 -234 ...
\verb|## $ accel_dumbbell_y : num    47    47    46    48    48    47    48    47    48    47    ...
##
   $ magnet_dumbbell_x : num -559 -555 -561 -552 -554 -549 -558 -554 -552 -554 ...
## $ magnet_dumbbell_y : num 293 296 298 303 292 292 291 291 302 294 ...
## $ magnet_dumbbell_z : num -65 -64 -63 -60 -68 -65 -69 -65 -69 -63 ...
## $ roll_forearm
                      : num 28.4 28.3 28.3 28.1 28 27.7 27.7 27.5 27.2 27.2 ...
## $ pitch_forearm
                      : num -63.9 -63.9 -63.9 -63.9 -63.8 -63.8 -63.8 -63.9 -63.9 ...
## $ yaw forearm : num -153 -153 -152 -152 -152 -152 -152 -151 -151 ...
## $ total_accel_forearm : num 36 36 36 36 36 36 36 36 36 36 ...
## $ gyros_forearm_y : num 0 0 -0.02 -0.02 0 0 0 0.02 0 -0.02 ...
## $ gyros_forearm_z : num -0.02 -0.02 0 0 -0.02 -0.02 -0.03 -0.03 -0.03 ...
## $ accel_forearm_x : num 192 192 196 189 189 193 190 191 193 192 ...
## $ accel_forearm_y : num 203 203 204 206 206 204 205 203 205 201 ...
                     : num -215 -216 -213 -214 -214 -214 -215 -215 -215 -214 ...
## $ accel_forearm_z
## $ magnet_forearm_x : num -17 -18 -18 -16 -17 -16 -22 -11 -15 -16 ...
## $ magnet_forearm_y
                      : num 654 661 658 658 655 653 656 657 655 656 ...
```

```
## [1] 13737 54
```

Pricipal component analysis

Check variable that are highly correlated with each other. It means a correlation coeffecient greater than 0.9

```
Cor<-abs(cor(training2[,c(-54)]))
diag(Cor)<-0
correlation = data.frame(which(Cor>0.90, arr.ind=T))
```

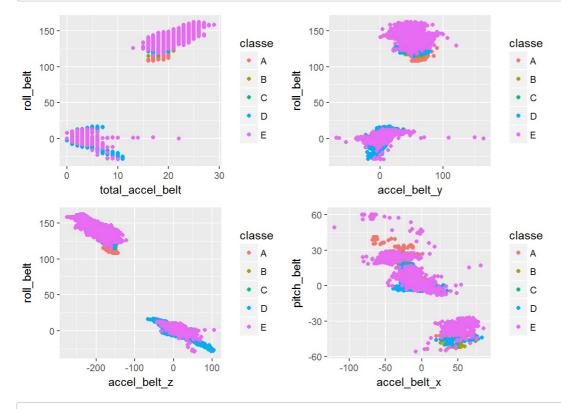
```
## Warning in data.row.names(row.names, rowsi, i): some row.names duplicated:
## 6,7,9,10,11,12,13,14,20,21,22 --> row.names NOT used
```

```
cor<-unique(correlation[,"row"])
which(Cor>0.90, arr.ind=T)
```

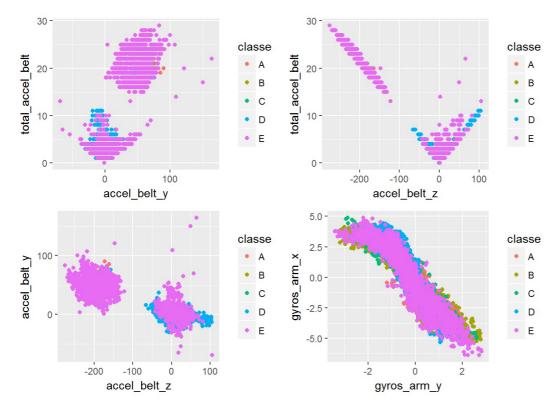
```
##
                     row col
## total_accel_belt
                       5
                           2
## accel_belt_y
                      10
## accel_belt_z
                      11
## accel belt x
## roll belt
## accel_belt_y
                      10
                      11
## accel_belt_z
## pitch_belt
                       .3
                           9
## roll belt
                       2
                          1.0
## total_accel_belt
                       5
                          10
## accel belt z
                      11
                          10
## roll belt
                       2
                          11
## total_accel_belt
                       5
                          11
## accel_belt_y
                      10
                          11
                      2.0
                          19
## gyros_arm_y
                      19
                          20
## gyros_arm_x
## gyros_dumbbell_z
                      34
                          32
## gyros forearm z
## gyros dumbbell x
## gyros_forearm_z
                      47
                      32
## gyros_dumbbell_x
                          47
## gyros_dumbbell_z
```

Plot some ghaphs to se how correlated some of theses variables are

```
plot1<-qplot(total_accel_belt, roll_belt, colour=classe, data=training2)
plot2<-qplot(accel_belt_y, roll_belt, colour=classe, data=training2)
plot3<-qplot(accel_belt_z, roll_belt, colour=classe, data=training2)
plot4<-qplot(accel_belt_x, pitch_belt, colour=classe, data=training2)
grid.arrange(plot1, plot2, plot3, plot4, ncol=2)</pre>
```

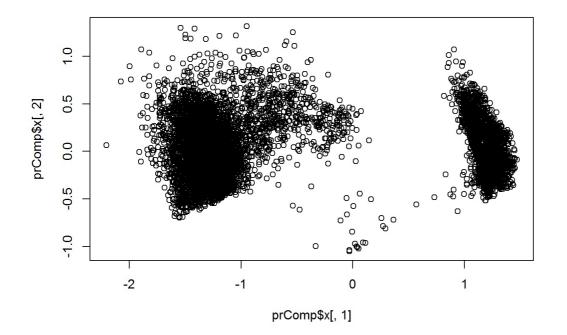


```
plot5<-qplot(accel_belt_y, total_accel_belt, colour=classe, data=training2)
plot6<-qplot(accel_belt_z, total_accel_belt, colour=classe, data=training2)
plot7<-qplot(accel_belt_z, accel_belt_y, colour=classe, data=training2)
plot8<-qplot(gyros_arm_y, gyros_arm_x, colour=classe, data=training2)
grid.arrange(plot5, plot6, plot7, plot8, ncol=2)</pre>
```



To avoid multicolinearity lets use PCA only for the variables that had high correlation with the others, reducing the data dimension

```
prComp<-prcomp(log10(abs(training2[,cor])+1))
plot(prComp$x[,1], prComp$x[,2])</pre>
```



```
preProc<-preProcess(log10(abs(training2[,cor])+1),method="pca",pcaComp=2)
PCA_train<-predict(preProc, log10(abs(training2[,cor])+1))
training3<-cbind(training2[,-cor],PCA_train)
str(training3); dim(training3)</pre>
```

```
## 'data.frame': 13737 obs. of 45 variables:
                 : num 11 11 11 12 12 12 12 12 12 12 ...
## $ num_window
                       : num -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 ...
## $ yaw_belt
                    ## $ gyros_belt_x
: num -0.02 -0.02 -0.02 0.02 0 -0.02 -0.02 0 -0.02 -0.03 ...
## $ total accel dumbbell: num 37 37 37 37 37 37 37 37 37 37 ...
## $ gyros_dumbbell_y : num -0.02 -0.02 -0.02 -0.02 -0.02 -0.02 -0.02 -0.02 -0.02 -0.02 ...
                        : num -234 -233 -232 -232 -233 -232 -235 -233 -234 -234 ...
##
   $ accel dumbbell x
## $ accel_dumbbell_y
                        : num 47 47 46 48 48 47 48 47 48 47 ...
## $ accel dumbbell z
                        : num -271 -269 -270 -269 -270 -269 -270 -270 -269 -270 ...
## $ magnet dumbbell x : num -559 -555 -561 -552 -554 -549 -558 -554 -552 -554 ...
## $ magnet_dumbbell_y : num 293 296 298 303 292 291 291 302 294 ...
## $ magnet_dumbbell_z : num -65 -64 -63 -60 -68 -65 -69 -65 -69 -63 ...
## $ roll_forearm : num 28.4 28.3 28.3 28.1 28 27.7 27.7 27.5 27.2 27.2 ...
: num -63.9 -63.9 -63.9 -63.9 -63.8 -63.8 -63.8 -63.9 -63.9 ...
## $ total_accel_forearm : num  36 36 36 36 36 36 36 36 36 36 36 ...
## $ gyros_forearm_y : num 0 0 -0.02 -0.02 0 0 0.02 0 -0.02 ...
## $ accel_forearm_x : num 192 192 196 189 189 193 190 191 193 192 ...
## $ accel_forearm_y : num 203 203 204 206 206 204 205 203 205 201 ...
## $ accel_forearm_z : num -215 -216 -213 -214 -214 -214 -215 -215 -215 -214 ...
## $ magnet_forearm_x : num -17 -18 -18 -16 -17 -16 -22 -11 -15 -16 ...
## $ magnet_forearm_y : num 654 661 658 658 655 653 656 657 655 656 ...
## $ magnet_forearm_z : num 476 473 469 469 473 476 473 478 472 472 ...
## $ classe
                       : Factor w/ 5 levels "A", "B", "C", "D", ...: 1 1 1 1 1 1 1 1 1 1 ...
## $ PC1
                       : num -1.65 -1.62 -1.6 -1.71 -1.75 ...
## $ PC2
                       : num 3.1 3.05 3.06 3.02 3.06 ...
```

```
## [1] 13737 45
```

Without look to testing dataset lets make the same transformation we did for training dataset

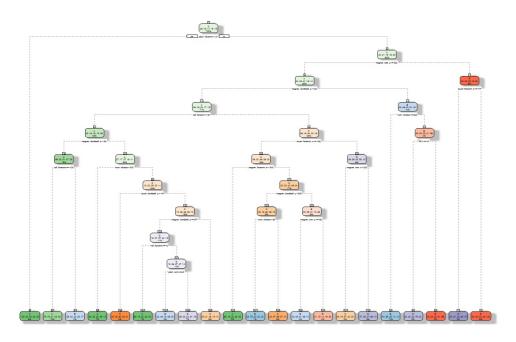
```
testing2 <- testing[, var_no_missing$var]
testing2 <- testing2[,-6]
testing2 <- testing2[, -c(1:5)]
testing2[integer$integ] <- lapply(testing2[integer$integ], as.numeric)
PCA_test<-predict(preProc, log10(abs(testing2[,cor])+1))
testing3<-cbind(testing2[,-cor],PCA_test)</pre>
```

Due to the poor performance obtained to adjust the models, the default parameters of the cross validation have been changed. The method of cross-validation was maintained, with the number of interactions being altered and allowing parallelism

```
options <- trainControl(method = "cv", number = 7, allowParallel=TRUE)</pre>
```

Adjusting different prediction algorithms.

 $\label{local_modFitA} $$ \ \ $$ modFitA <- \ part(training3$classe $$ \sim ., \ data=training3, \ method="class")$ $$ fancyRpartPlot(modFitA) $$$



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```
predFitA<-predict(modFitA, testing3, type = "class")
mA<-confusionMatrix(testing3$classe, predFitA)</pre>
```

Random Forest

```
modFitB <- randomForest(classe ~. , data= training3)
predFitB<-predict(modFitB, testing3)
mB<-confusionMatrix(testing3$classe, predFitB)</pre>
```

Boosting

```
modFitC <- train(classe ~ ., data = training3, method = "LogitBoost", trControl= options)
predFitC<-predict(modFitC, testing3)
mC<-confusionMatrix(testing3$classe, predFitC)</pre>
```

Linear Descriminant Analysis

```
modFitD <- train(classe~., data=training3, method="lda", trControl= options)
predFitD<-predict(modFitD, testing3)
mD<-confusionMatrix(testing3$classe, predFitD)</pre>
```

Naive Bayes

```
modFitE <- train(classe~., data=training3, method="nb", trControl= options)
predFitE<-predict(modFitE, testing3)
mE<-confusionMatrix(testing3$classe, predFitE)</pre>
```

Bagging

```
modFitF <- train(classe~., data=training3, method="treebag", trControl= options)
predFitF<-predict(modFitF, testing3)
mF<-confusionMatrix(testing3$classe, predFitF)</pre>
```

Comparing results of algorithms

```
## Accuracy "Decision Tree" "0.688870008496177"
## Accuracy "Random Forest" "0.9964316057774"
## Accuracy "LogitBoost" "0.928878468151622"
## Accuracy "Linear Descriminant Analysis" "0.678164825828377"
## Accuracy "Naive Bayes" "0.763296516567545"
## Accuracy "Bagging" "0.990314358538658"
```

Combining predictors

Build a dataset with the results of predictions.

Boosting won't be used because generated a lot os missing value

Use the Random Forest to adjust a model based in the result of the previous models (modFitComb)

```
modFitComb <- randomForest(classe ~. , data= combDF)</pre>
```

Without look to validation dataset lets make the same transformation we did for training dataset

```
validation2 <- validation[, var_no_missing$var]
validation2 <- validation2[,-6]
validation2 <- validation2[, -c(1:5)]
validation2[integer$integ] <- lapply(validation2[integer$integ], as.numeric)
PCA_valid<-predict(preProc, log10(abs(validation2[,cor])+1))
validation3<-cbind(validation2[,-cor],PCA_valid)</pre>
```

Builing a dataset for validation with the prediction of each algorithm

```
predAV<-predict(modFitA, validation3, type = "class");
predBV<-predict(modFitB, validation3);
predCV<-predict(modFitC, validation3); predDV<-predict(modFitD, validation3);
predEV<-predict(modFitE, validation3); predFV<-predict(modFitF, validation3);
CombValid<-data.frame(predA=predAV, predB=predBV, predD=predDV, predE=predEV, predF=predFV)</pre>
```

Using the combined predictors (modFitComb) to predict classe for validation dataset

```
predFitComb<-predict(modFitComb, CombValid)
predFitComb</pre>
```

```
## 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
```