# Prediction Assignment Writeup

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```
library(tinytex)
library(ggplot2)
library(dplyr)
library(caret)
library(randomForest)

library(doParallel)
cluster <- makeCluster(3)
registerDoParallel(cluster)</pre>
```

### Data importation

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

### Cleaning Data

```
training_C <- select(training, -contains('timestamp'))
training_C <- select(training_C, -"X")
training_C <- select(training_C, -"user_name")
training_C <- select(training_C, -"new_window")
training_C <- training_C[,colSums(is.na(training_C)) == 0]

testing_C <- select(testing, -contains('timestamp'))
testing_C <- select(testing_C, -"X")
testing_C <- select(testing_C, -"user_name")
testing_C <- select(testing_C, -"new_window")
testing_C <- testing_C[,colSums(is.na(testing_C)) == 0]</pre>
```

## Modeling

## Model split

I have split the data in 70% for training.

```
set.seed(10)
inTrain <- createDataPartition(training_C$classe, p=0.7, list=F)
trainingPart <- training_C[inTrain,]
testingPart <- training_C[-inTrain,]</pre>
```

### training Model

I will compare different solution.

```
start_time <- Sys.time()
model_gbm <- train(classe ~ ., data=trainingPart, method="gbm", verbose=T)</pre>
```

#### Generalized Boosted Regression

```
## Iter
          TrainDeviance
                          ValidDeviance
                                           StepSize
                                                      Improve
##
                 1.6094
                                             0.1000
                                                       0.2417
        1
                                     nan
##
        2
                                             0.1000
                                                       0.1625
                 1.4565
                                     nan
##
        3
                                                       0.1274
                 1.3535
                                             0.1000
                                     nan
        4
                                             0.1000
                                                       0.0919
##
                 1.2706
                                     nan
        5
##
                 1.2108
                                     nan
                                             0.1000
                                                       0.0984
##
        6
                 1.1498
                                     nan
                                             0.1000
                                                       0.0813
##
        7
                                                       0.0705
                 1.0981
                                     nan
                                             0.1000
##
        8
                 1.0542
                                             0.1000
                                                       0.0633
                                     nan
        9
##
                 1.0133
                                     nan
                                             0.1000
                                                       0.0633
##
       10
                 0.9735
                                             0.1000
                                                       0.0478
                                     nan
##
       20
                 0.7071
                                     nan
                                             0.1000
                                                       0.0285
##
       40
                 0.4689
                                             0.1000
                                                       0.0145
                                     nan
##
       60
                 0.3353
                                             0.1000
                                                       0.0063
                                     nan
##
                                             0.1000
                                                       0.0052
       80
                 0.2539
                                     nan
##
      100
                 0.1958
                                             0.1000
                                                       0.0027
                                     nan
                                             0.1000
##
      120
                 0.1561
                                                       0.0023
                                     nan
##
      140
                 0.1254
                                             0.1000
                                                       0.0012
                                     nan
##
      150
                 0.1125
                                             0.1000
                                                       0.0026
                                     nan
```

```
end_time <- Sys.time()
accuracy.gbm <- model_gbm$results$Accuracy[as.integer(row.names(model_gbm$bestTune))]
errorRate.gbm <- model_gbm$finalModel$err.rate[model_gbm$finalModel$ntree,1]
time.gmb<-end_time-start_time</pre>
```

```
start_time <- Sys.time()
model_rf <- train(classe ~ ., data=trainingPart, method='rf', verbose=T)
end_time <- Sys.time()
accuracy.rf <- model_rf$results$Accuracy[as.integer(row.names(model_rf$bestTune))]</pre>
```

```
errorRate.rf <- model_rf$finalModel$err.rate[model_rf$finalModel$ntree,1]
time.rf<-end_time-start_time</pre>
```

#### Random Forest

### Choose of the training model

```
a<-matrix(c(accuracy.rf,errorRate.rf,time.rf,accuracy.gbm,errorRate.gbm,time.gmb),nrow=3)

## Warning in matrix(c(accuracy.rf, errorRate.rf, time.rf, accuracy.gbm,
## errorRate.gbm, : la longueur des données [5] n'est pas un diviseur ni un
## multiple du nombre de lignes [3]

dimnames(a)=list(c("accuracy","error","exe time"),c("rf","gbm"))
a

## rf gbm
## accuracy 0.995860836 0.9834894
## error 0.002475067 10.9568169
## exe time 23.828341266 0.9958608</pre>
```

The best prediction is with the random forest.

## Conclusion

We will use the random forest to answer the quiz.

## Prediciton for the testing data

```
quiz_answer<-predict(model_rf$finalModel, newdata=testing_C)
quiz_answer</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