

# Deel\_Practical Machine Learning\_Course Project

*Jakob Deel*

*November 11, 2018*

## Executive Summary

Using data from wearable workout technology, this project builds and tests a machine learning algorithm to predict the level of quality with which an exercise was conducted ("classe"). The optimal model was a boosted generalized linear model, with an estimated very low out of sample error.

```
#sets working directory and removes unnecessary objects
setwd("C:/Users/jdeel/Documents/Training/JHU - Coursera/Practical Machine Learning/Course Project")
rm(list = ls())
```

```
library(AppliedPredictiveModeling)
library(caret)
```

```
## Loading required package: lattice
```

```
## Loading required package: ggplot2
```

```
library(ElemStatLearn)
library(pgmm)
library(rpart)
library(gbm)
```

```
## Loaded gbm 2.1.4
```

```
library(lubridate)
```

```
##
## Attaching package: 'lubridate'
```

```
## The following object is masked from 'package:base':
##
##   date
```

```
library(forecast)
library(e1071)
library(randomForest)
```

```
## randomForest 4.6-14
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

```
##
## Attaching package: 'randomForest'
```

```
## The following object is masked from 'package:ggplot2':
##
##     margin
```

## Data Loading and Processing

The following data loads the provided training and test datasets and filters out the fields that are more than 75% missing data.

```
#Loads data
trainingraw = read.csv("pml-training.csv",na.strings=c("NA",""))
testingraw = read.csv("pml-testing.csv",na.strings=c("NA",""))

#filters out dimensions from training and test sets where most values are NA
trainNAs <- apply(trainingraw, 2, function(x) {
  sum(is.na(x))
})

mostNAstrain <- trainNAs>(0.75*dim(trainingraw[1]))

goodfieldstraining <- subset(names(mostNAstrain),mostNAstrain==FALSE)

training <- subset(trainingraw,select=goodfieldstraining)

testNAs <- apply(testingraw, 2, function(x) {
  sum(is.na(x))
})

mostNAstest <- testNAs>(0.75*dim(testingraw[1]))

goodfieldstest <- subset(names(mostNAstest),mostNAstest==FALSE)
testing <- testingraw[,goodfieldstest]
```

# Model Building and Cross-Validation

The following data builds two models, a random forest and boosted model, and tests each using 3-fold cross validation to maximize accuracy. Though both models results in high accuracy, the boosted model is better and is therefore selected for use

```
#sets seed for reproducibility
set.seed(123)

#creates models using random forest and boosting, testing each using 3-fold cross validation
# Define training control
train.control <- trainControl(method = "cv", number = 3)

# Train the random forest model
forestmodel <- train(classe~.,data=training,method="rf",
                     trControl = train.control,na.action=na.omit)
# Summarize the results
print(forestmodel)
```

```
## Random Forest
##
## 19622 samples
##    59 predictor
##    5 classes: 'A', 'B', 'C', 'D', 'E'
##
## No pre-processing
## Resampling: Cross-Validated (3 fold)
## Summary of sample sizes: 13081, 13082, 13081
## Resampling results across tuning parameters:
##
##  mtry  Accuracy   Kappa
##    2    0.9954643 0.9942628
##   41    0.9998981 0.9998711
##   81    0.9997961 0.9997422
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 41.
```

```
# Train the boosting model
boostedmodel <- train(classe~.,data=training,method="gbm",
                     trControl = train.control,na.action=na.omit)
```

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.4544
##	2	1.3252	nan	0.1000	0.3110
##	3	1.1324	nan	0.1000	0.2402
##	4	0.9841	nan	0.1000	0.1978
##	5	0.8625	nan	0.1000	0.1587
##	6	0.7635	nan	0.1000	0.1447
##	7	0.6750	nan	0.1000	0.1229
##	8	0.6001	nan	0.1000	0.1081
##	9	0.5345	nan	0.1000	0.0890
##	10	0.4788	nan	0.1000	0.0845
##	20	0.1648	nan	0.1000	0.0263
##	40	0.0236	nan	0.1000	0.0035
##	60	0.0039	nan	0.1000	0.0004
##	80	0.0009	nan	0.1000	0.0000
##	100	0.0003	nan	0.1000	0.0000
##	120	0.0001	nan	0.1000	0.0000
##	140	0.0000	nan	0.1000	0.0000
##	150	0.0000	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.7755
##	2	1.1448	nan	0.1000	0.4623
##	3	0.8699	nan	0.1000	0.3209
##	4	0.6790	nan	0.1000	0.2375
##	5	0.5377	nan	0.1000	0.1814
##	6	0.4296	nan	0.1000	0.1413
##	7	0.3454	nan	0.1000	0.1116
##	8	0.2789	nan	0.1000	0.0887
##	9	0.2258	nan	0.1000	0.0712
##	10	0.1833	nan	0.1000	0.0572
##	20	0.0241	nan	0.1000	0.0073
##	40	0.0007	nan	0.1000	0.0001
##	60	0.0000	nan	0.1000	0.0000
##	80	0.0000	nan	0.1000	0.0000
##	100	0.0000	nan	0.1000	0.0000
##	120	0.0000	nan	0.1000	0.0000
##	140	0.0000	nan	0.1000	0.0000
##	150	0.0000	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.7757
##	2	1.1447	nan	0.1000	0.4621
##	3	0.8700	nan	0.1000	0.3210
##	4	0.6790	nan	0.1000	0.2374
##	5	0.5377	nan	0.1000	0.1813
##	6	0.4297	nan	0.1000	0.1411
##	7	0.3455	nan	0.1000	0.1114

##	8	0.2789	nan	0.1000	0.0886
##	9	0.2259	nan	0.1000	0.0710
##	10	0.1835	nan	0.1000	0.0573
##	20	0.0242	nan	0.1000	0.0072
##	40	0.0005	nan	0.1000	0.0001
##	60	0.0000	nan	0.1000	0.0000
##	80	0.0000	nan	0.1000	0.0000
##	100	0.0000	nan	0.1000	0.0000
##	120	0.0000	nan	0.1000	0.0000
##	140	0.0000	nan	0.1000	0.0000
##	150	0.0000	nan	0.1000	-0.0000

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.4532
##	2	1.3255	nan	0.1000	0.3098
##	3	1.1323	nan	0.1000	0.2418
##	4	0.9835	nan	0.1000	0.1977
##	5	0.8618	nan	0.1000	0.1581
##	6	0.7630	nan	0.1000	0.1443
##	7	0.6748	nan	0.1000	0.1224
##	8	0.6004	nan	0.1000	0.1081
##	9	0.5345	nan	0.1000	0.0893
##	10	0.4793	nan	0.1000	0.0849
##	20	0.1649	nan	0.1000	0.0262
##	40	0.0235	nan	0.1000	0.0032
##	60	0.0039	nan	0.1000	0.0006
##	80	0.0009	nan	0.1000	0.0001
##	100	0.0002	nan	0.1000	0.0000
##	120	0.0001	nan	0.1000	0.0000
##	140	0.0000	nan	0.1000	0.0000
##	150	0.0000	nan	0.1000	0.0000

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.7769
##	2	1.1447	nan	0.1000	0.4614
##	3	0.8700	nan	0.1000	0.3211
##	4	0.6790	nan	0.1000	0.2377
##	5	0.5377	nan	0.1000	0.1813
##	6	0.4297	nan	0.1000	0.1414
##	7	0.3454	nan	0.1000	0.1115
##	8	0.2788	nan	0.1000	0.0887
##	9	0.2258	nan	0.1000	0.0711
##	10	0.1833	nan	0.1000	0.0571
##	20	0.0241	nan	0.1000	0.0073
##	40	0.0006	nan	0.1000	0.0002
##	60	0.0001	nan	0.1000	0.0000
##	80	0.0000	nan	0.1000	-0.0000
##	100	0.0000	nan	0.1000	-0.0000
##	120	0.0000	nan	0.1000	-0.0000

```

##      140      0.0000      nan      0.1000 -0.0000
##      150      0.0000      nan      0.1000  0.0000
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.6094      nan      0.1000   0.7747
##      2      1.1447      nan      0.1000   0.4619
##      3      0.8699      nan      0.1000   0.3213
##      4      0.6789      nan      0.1000   0.2376
##      5      0.5377      nan      0.1000   0.1811
##      6      0.4297      nan      0.1000   0.1413
##      7      0.3454      nan      0.1000   0.1116
##      8      0.2789      nan      0.1000   0.0889
##      9      0.2258      nan      0.1000   0.0711
##     10      0.1833      nan      0.1000   0.0572
##     20      0.0241      nan      0.1000   0.0073
##     40      0.0005      nan      0.1000   0.0001
##     60      0.0000      nan      0.1000   0.0000
##     80      0.0000      nan      0.1000  -0.0000
##    100      0.0000      nan      0.1000   0.0000
##    120      0.0000      nan      0.1000   0.0000
##    140      0.0000      nan      0.1000  -0.0000
##    150      0.0000      nan      0.1000  -0.0000
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.6094      nan      0.1000   0.4544
##      2      1.3253      nan      0.1000   0.3111
##      3      1.1319      nan      0.1000   0.2402
##      4      0.9832      nan      0.1000   0.1980
##      5      0.8615      nan      0.1000   0.1587
##      6      0.7629      nan      0.1000   0.1445
##      7      0.6746      nan      0.1000   0.1223
##      8      0.5998      nan      0.1000   0.1079
##      9      0.5340      nan      0.1000   0.0890
##     10      0.4787      nan      0.1000   0.0844
##     20      0.1658      nan      0.1000   0.0281
##     40      0.0236      nan      0.1000   0.0034
##     60      0.0039      nan      0.1000   0.0006
##     80      0.0008      nan      0.1000   0.0001
##    100      0.0002      nan      0.1000   0.0000
##    120      0.0000      nan      0.1000   0.0000
##    140      0.0000      nan      0.1000   0.0000
##    150      0.0000      nan      0.1000   0.0000
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.6094      nan      0.1000   0.7765
##      2      1.1446      nan      0.1000   0.4614
##      3      0.8698      nan      0.1000   0.3211
##      4      0.6789      nan      0.1000   0.2372
##      5      0.5376      nan      0.1000   0.1814

```

##	6	0.4295	nan	0.1000	0.1411
##	7	0.3452	nan	0.1000	0.1115
##	8	0.2787	nan	0.1000	0.0887
##	9	0.2257	nan	0.1000	0.0711
##	10	0.1832	nan	0.1000	0.0572
##	20	0.0240	nan	0.1000	0.0073
##	40	0.0004	nan	0.1000	0.0001
##	60	0.0000	nan	0.1000	0.0000
##	80	0.0000	nan	0.1000	-0.0000
##	100	0.0000	nan	0.1000	-0.0000
##	120	0.0000	nan	0.1000	-0.0000
##	140	0.0000	nan	0.1000	0.0000
##	150	0.0000	nan	0.1000	-0.0000

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.7765
##	2	1.1447	nan	0.1000	0.4603
##	3	0.8699	nan	0.1000	0.3212
##	4	0.6789	nan	0.1000	0.2372
##	5	0.5376	nan	0.1000	0.1809
##	6	0.4296	nan	0.1000	0.1413
##	7	0.3454	nan	0.1000	0.1113
##	8	0.2789	nan	0.1000	0.0887
##	9	0.2259	nan	0.1000	0.0710
##	10	0.1834	nan	0.1000	0.0573
##	20	0.0242	nan	0.1000	0.0072
##	40	0.0005	nan	0.1000	0.0001
##	60	0.0000	nan	0.1000	0.0000
##	80	0.0000	nan	0.1000	0.0000
##	100	0.0000	nan	0.1000	-0.0000
##	120	0.0000	nan	0.1000	-0.0000
##	140	0.0000	nan	0.1000	-0.0000
##	150	0.0000	nan	0.1000	-0.0000

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.7777
##	2	1.1447	nan	0.1000	0.4619
##	3	0.8699	nan	0.1000	0.3210
##	4	0.6789	nan	0.1000	0.2375
##	5	0.5376	nan	0.1000	0.1813
##	6	0.4296	nan	0.1000	0.1411
##	7	0.3453	nan	0.1000	0.1114
##	8	0.2788	nan	0.1000	0.0888
##	9	0.2258	nan	0.1000	0.0710
##	10	0.1833	nan	0.1000	0.0572
##	20	0.0241	nan	0.1000	0.0073
##	40	0.0005	nan	0.1000	0.0001
##	50	0.0001	nan	0.1000	0.0000

```
# Summarize the results
print(boostedmodel)
```

```
## Stochastic Gradient Boosting
##
## 19622 samples
##    59 predictor
##    5 classes: 'A', 'B', 'C', 'D', 'E'
##
## No pre-processing
## Resampling: Cross-Validated (3 fold)
## Summary of sample sizes: 13080, 13082, 13082
## Resampling results across tuning parameters:
##
##  interaction.depth  n.trees  Accuracy  Kappa
##    1                50      0.9997961  0.9997422
##    1               100      0.9997452  0.9996777
##    1               150      0.9996942  0.9996132
##    2                50      0.9997961  0.9997422
##    2               100      0.9997961  0.9997422
##    2               150      0.9997961  0.9997422
##    3                50      0.9998981  0.9998711
##    3               100      0.9998471  0.9998066
##    3               150      0.9997961  0.9997422
##
## Tuning parameter 'shrinkage' was held constant at a value of 0.1
##
## Tuning parameter 'n.minobsinnode' was held constant at a value of 10
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were n.trees = 50, interaction.depth
## = 3, shrinkage = 0.1 and n.minobsinnode = 10.
```

```
# boosted has better accuracy in CV (0.99999 in optimal model vs. 0.9999 in optimal fo
rest model), so that's one is used
```

## Out of Sample Error Estimation

The following code runs the model on a randomly-selected third of the training dataset and checks the accuracy to estimate out of sample error. Though not a perfect test, the fact that the accuracy is 100% means that we should expect very low out of sample error.



```
#runs boosted model on random third of training set to estimate out of sample error
oostrainsample <- training$classe %>%
  createDataPartition(p = 0.33, list = FALSE)

oostraining <- training[oostrainsample,]

oostraining$boostedpreds <- predict(boostedmodel,oostraining)
oostraining$boostedright <- oostraining$classe==oostraining$boostedpreds

#estimates out of sample error
mean(oostraining$boostedright)
```

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