

# Practical Machine Learning Project

Louis Jordan

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## Executive Summary

Participants in the Human Activity Recognition (HAR) Project were asked to perform various exercises correctly and incorrectly in 5 different ways. Using performance data collected from accelerometers fed by multiple quantified self movement devices, the goal of this project is to train a model that could be used to predict the manner in which the participants performed the exercises.

The data for this project come from this source: <http://groupware.les.inf.puc-rio.br/har>.

The training data for this project are available here:

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

The test data for this project are available here:

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

## Preliminaries

### Set Seed for Reproducibility

#### Load Required Libraries

```
print(currentDate <- date())  
## [1] "Sat Apr 16 20:48:01 2016"  
  
set.seed(212061996)  
library(caret)  
library(gmodels)  
library(randomForest)
```

#### Load the Data Sets

```
trainChunk <- read.csv("pmlTrain.csv", header = TRUE, stringsAsFactors = FALSE,  
                      sep = ",", na.strings = c("NA", "", "#DIV/0!"))  
  
testChunk <- read.csv("pmlTest.csv", header = TRUE, stringsAsFactors = FALSE,  
                    sep = ",", na.strings = c("NA", "", "#DIV/0!"))  
  
trainChunk$classe <- as.factor(trainChunk$classe)
```

## Preprocess (Examine & Clean) the Data

Remove missing values, irrelevant columns of data, and other items from the data set that do not contribute to the scope of the project

### Examine the Data

```
# summary(trainChunk)
# str(trainChunk)
dim(trainChunk)

## [1] 19622 160
```

### Remove RowID Column

```
removeIDCol <- trainChunk[, -1]
processedTrainChunk <- removeIDCol
dim(processedTrainChunk)

## [1] 19622 159
```

### Find & Remove Missing Values

```
NAs <- apply(processedTrainChunk, 2, function(x) {sum(is.na(x))})
removeNAs <- processedTrainChunk[, which (NAs == 0)]
processedTrainChunk <- removeNAs
dim(processedTrainChunk)

## [1] 19622 59
```

### Remove NZV Values

```
removeNZV <- nearZeroVar(processedTrainChunk)
processedTrainChunk <- processedTrainChunk[, -removeNZV]
dim(processedTrainChunk)

## [1] 19622 58
```

### Find & Remove Useless Predictors (features)

```
uselessPredictors <- grep("cvtd_timestamp|X|user_name|num_window",
                          names (trainChunk))
processedTrainChunk <- processedTrainChunk[, -uselessPredictors]
dim(processedTrainChunk)

## [1] 19622 54
```

## Define Data Partitions

### Partition Training Data into Training and Validating Data Subsets

```
inTrain <- createDataPartition(y = trainChunk$classe, p = 0.25, list = FALSE)
training <- processedTrainChunk[inTrain, ]
dim(training)

## [1] 4907    54

# create test data for future use in cross validation
validating <- processedTrainChunk[-inTrain, ]
dim(validating)

## [1] 14715    54
```

## Modeling

### Fit the Model Using the Random Forest Algorithm (5-fold cross validation)

```
ctrl <- trainControl(method = "cv", number = 5, allowParallel = TRUE)
myModel <- train(training$classe ~ ., data = training, method = "rf",
  prof = TRUE, trControl = ctrl)
myModel

## Random Forest
##
## 4907 samples
## 53 predictor
## 5 classes: 'A', 'B', 'C', 'D', 'E'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 3925, 3925, 3927, 3926, 3925
## Resampling results across tuning parameters:
##
##  mtry Accuracy Kappa
##  2    0.9606698 0.9501931
## 36    0.9743223 0.9674952
## 71    0.9698371 0.9618124
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 36.
```

## Evaluate the Model

```
cvPrediction <- predict(myModel, newdata = validating)
confusionMatrix(cvPrediction, validating$classe)

## Confusion Matrix and Statistics
##
##              Reference
## Prediction    A    B    C    D    E
##      A 4180    35     0     0     0
##      B     3 2739    70     0     0
##      C     2   73 2469    28     6
##      D     0     0   27 2370    11
##      E     0     0     0   14 2688
##
## Overall Statistics
##
##              Accuracy : 0.9817
##              95% CI : (0.9794, 0.9838)
##      No Information Rate : 0.2844
##      P-Value [Acc > NIR] : < 2.2e-16
##
##              Kappa : 0.9769
##  McNemar's Test P-Value : NA
##
## Statistics by Class:
##
##              Class: A Class: B Class: C Class: D Class: E
## Sensitivity          0.9988  0.9621  0.9622  0.9826  0.9937
## Specificity          0.9967  0.9938  0.9910  0.9969  0.9988
## Pos Pred Value       0.9917  0.9740  0.9577  0.9842  0.9948
## Neg Pred Value       0.9995  0.9909  0.9920  0.9966  0.9986
## Prevalence           0.2844  0.1935  0.1744  0.1639  0.1838
## Detection Rate       0.2841  0.1861  0.1678  0.1611  0.1827
## Detection Prevalence 0.2864  0.1911  0.1752  0.1636  0.1836
## Balanced Accuracy    0.9977  0.9780  0.9766  0.9897  0.9963

cvPrediction <- predict(myModel, newdata = validating)
accuracy <- c(as.numeric(cvPrediction == validating$classe))
accuracy <- sum(accuracy) * 100/nrow(validating)
oosError <- 100 - accuracy
```

The CrossTable function of the gmodels package yields a more detailed confusion matrix.

```
CrossTable(cvPrediction, validating$classe)

##
##   Cell Contents
## |-----|
## |                N
## | Chi-square contribution
## |      N / Row Total
## |      N / Col Total
## |      N / Table Total
## |-----|
##
##
## Total Observations in Table:  14715
##
##
```

cvPrediction	validating\$classe					Row Total
	A	B	C	D	E	
A	4180	35	0	0	0	4215
	7414.138	747.004	735.011	690.899	774.827	
	0.992	0.008	0.000	0.000	0.000	0.286
	0.999	0.012	0.000	0.000	0.000	
	0.284	0.002	0.000	0.000	0.000	
B	3	2738	70	0	0	2811
	793.470	8851.975	360.178	460.763	516.735	
	0.001	0.974	0.025	0.000	0.000	0.191
	0.001	0.962	0.027	0.000	0.000	
	0.000	0.186	0.005	0.000	0.000	
C	2	74	2469	28	6	2579
	729.483	361.949	9066.567	368.590	462.163	
	0.001	0.029	0.957	0.011	0.002	0.175
	0.000	0.026	0.962	0.012	0.002	
	0.000	0.005	0.168	0.002	0.000	
D	0	0	27	2370	11	2408
	684.844	465.890	367.643	9885.305	420.926	
	0.000	0.000	0.011	0.984	0.005	0.164
	0.000	0.000	0.011	0.983	0.004	
	0.000	0.000	0.002	0.161	0.001	
E	0	0	0	14	2688	2702
	768.459	522.772	471.174	415.339	9667.455	
	0.000	0.000	0.000	0.005	0.995	0.184
	0.000	0.000	0.000	0.006	0.994	
	0.000	0.000	0.000	0.001	0.183	
Column Total	4185	2847	2566	2412	2705	14715
	0.284	0.193	0.174	0.164	0.184	

```
##
##
```

## Predictions

### Predict on Test Data & Write to File

```
tcPrediction <- predict(myModel, testChunk, type = "raw")
tcPrediction

## [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

pml_write_files = function(x){
  n = length(x)
  for(i in 1:n) {
    filename = paste0("problem_id_", i, ".txt")
    write.table(x[i], file = filename, quote = FALSE, row.names = FALSE,
               col.names = FALSE)
  }
}

pml_write_files(tcPrediction)
```

## Conclusion

The kappa statistic ranges from 0 to 1, inclusive, with 1 indicating perfect agreement between the model's prediction and the true values. Though the interpretation can be subjective, generally speaking, a good agreement typically ranges between 0.60 - 0.80.

The model accuraccy is 98.17 %.

The out-of-sample error is 1.83 %.

The kappa value is 0.97.

```
print(currentDate <- date())
```

```
## [1] "Sat Apr 16 20:52:46 2016"
```