Predicting The Manner Of Exercise

Jerry Kiely

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The Introduction

This project looks at a HAR dataset:

> Human Activity Recognition - HAR - has emerged as a key research area in the last years and is gaining increasing attention by the pervasive computing research community, especially for the development of context-aware systems.

From the project brief:

> Using devices such as Jawbone Up, Nike FuelBand, and Fitbit it is now possible to collect a large amount of data about personal activity relatively inexpensively. These type of devices are part of the quantified self movement – a group of enthusiasts who take measurements about themselves regularly to improve their health, to find patterns in their behavior, or because they are tech geeks.

Relating to the current task:

> One thing that people regularly do is quantify how much of a particular activity they do, but they rarely quantify how well they do it. In this project, your goal will be to use data from accelerometers on the belt, forearm, arm, and dumbell of 6 participants. They were asked to perform barbell lifts correctly and incorrectly in 5 different ways.

We will attempt to predict the manner in which participants performed barbell lifts. We will do this by training a classifier with the provided dataset.

The Data

First we load the data:

```
    train <- read.csv('pml-training.csv', na.strings = c('NA', ''));
    test  <- read.csv('pml-testing.csv',  na.strings = c('NA', ''));
```

Next we clean the data by removing any columns that contain null data:

```
    nas   <- colSums(is.na(train)) > 0;

    names <- colnames(train);
    cols  <- names[!nas];
    train <- train[, cols];

    names <- colnames(test);
    cols  <- names[!nas];
    test  <- test[, cols];
```

Next we remove columns for predictors with nearly zero variance - i.e. columns that are almost constant and which are unlikely to affect the outcome:

```
    zvs   <- nearZeroVar(train);

    train <- train[, -zvs];
    test  <- test[, -zvs];
```

Then we ommit the first five columns (which contain index, user, and timestamp information):

```
    names[1:5];
```

```
## [1] "X"                    "user_name"            "raw_timestamp_part_1"
## [4] "raw_timestamp_part_2" "cvtd_timestamp"
```

```
    train <- train[, 6:ncol(train)];
    test  <- test[, 6:ncol(test)];
```

Now we can split the training data into two sets - for training and cross validation:

```
    partition <- createDataPartition(y = train$classe, p = 0.8, list = FALSE);
    part_tr   <- train[partition, ];
    part_cv   <- train[-partition, ];
```

The Training

Now we go straight into building our model - I choose to use a random forest due to the number of predictors, with classe as the outcome, and everything else as predictors.

Note: in truth we don't need to perform cross validation as the random forest does this internally - we do so only see how well the model performs in terms of estimating out of sample error - anything less than 1% should be acceptable:

```
    model <- train(
        classe ~ .,
        method = 'rf',
        data = part_tr,
        trControl = trainControl(method = 'oob', number = 4)
    );
```

Lets have a look at our model:

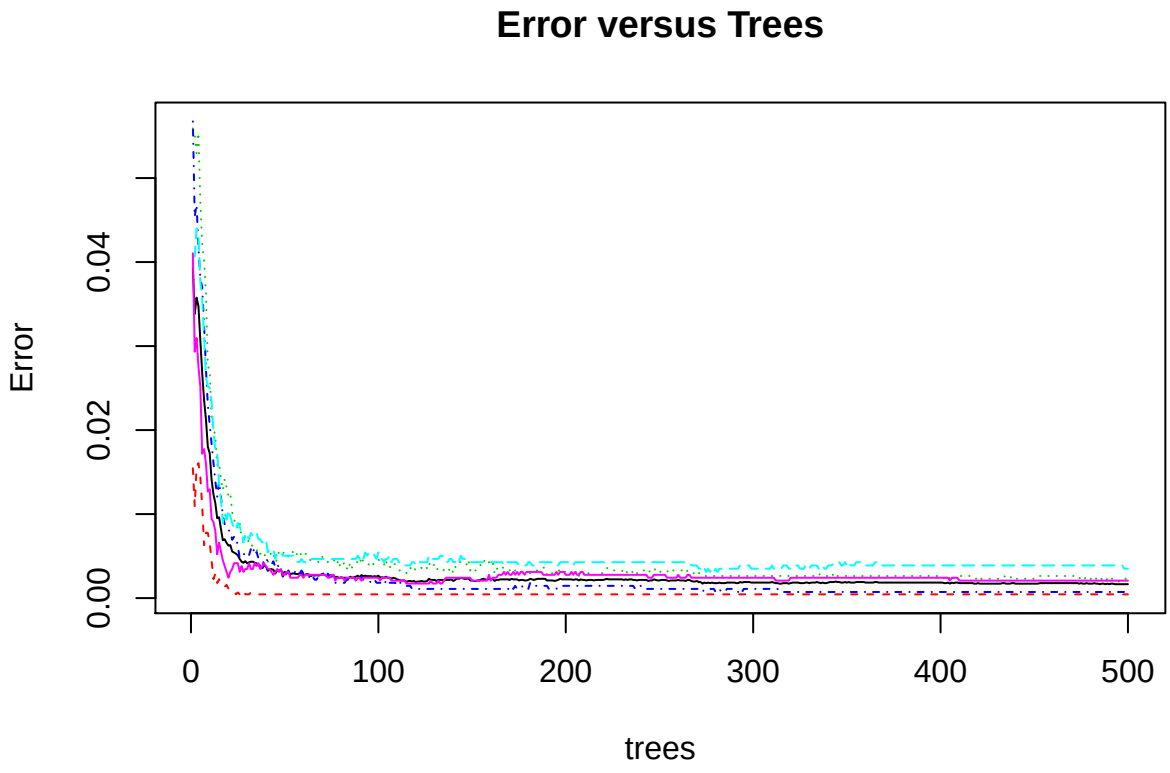
```
    model;
```

```
## Random Forest
##
## 15699 samples
##    53 predictor
##     5 classes: 'A', 'B', 'C', 'D', 'E'
##
## No pre-processing
```

```
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa
##    2    0.9962418  0.9952461
##   27    0.9982164  0.9977440
##   53    0.9963055  0.9953268
##
## Accuracy was used to select the optimal model using  the largest value.
## The final value used for the model was mtry = 27.
```

Lets plot the error of the model versus number of trees:

```
    plot(model$finalModel, main = 'Error versus Trees');
```



Clearly the error reduces sharply as the number of trees incresese, until around 50 trees, and then not significantly. Now we look at how the model fares against the training data, and the cross validation data:

```
    predict_tr <- predict(model, part_tr);
    cm_tr      <- confusionMatrix(predict_tr, part_tr$classe);

    predict_cv <- predict(model, part_cv);
    cm_cv      <- confusionMatrix(predict_cv, part_cv$classe);
```

Looking at the confusion matrix for the predictions of the training set:

```
    cm_tr;
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 4464    0    0    0    0
##          B    0 3038    0    0    0
##          C    0    0 2738    0    0
##          D    0    0    0 2573    0
##          E    0    0    0    0 2886
##
## Overall Statistics
##
##                Accuracy : 1
##                  95% CI : (0.9998, 1)
##     No Information Rate : 0.2843
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 1
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   1.0000   1.0000   1.0000   1.0000
## Specificity            1.0000   1.0000   1.0000   1.0000   1.0000
## Pos Pred Value         1.0000   1.0000   1.0000   1.0000   1.0000
## Neg Pred Value         1.0000   1.0000   1.0000   1.0000   1.0000
## Prevalence             0.2843   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2843   0.1935   0.1744   0.1639   0.1838
## Detection Prevalence   0.2843   0.1935   0.1744   0.1639   0.1838
## Balanced Accuracy      1.0000   1.0000   1.0000   1.0000   1.0000
```

we see an accuracy of 100%, as expected. Looking at the confusion matrix for the predictions of the cross validation set:

```
    cm_cv;
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1116    1    0    0    0
##          B    0  758    4    0    0
##          C    0    0  680    1    0
##          D    0    0    0  642    1
##          E    0    0    0    0  720
##
## Overall Statistics
##
##                Accuracy : 0.9982
##                  95% CI : (0.9963, 0.9993)
```

```
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9977
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   0.9987   0.9942   0.9984   0.9986
## Specificity            0.9996   0.9987   0.9997   0.9997   1.0000
## Pos Pred Value         0.9991   0.9948   0.9985   0.9984   1.0000
## Neg Pred Value         1.0000   0.9997   0.9988   0.9997   0.9997
## Prevalence             0.2845   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2845   0.1932   0.1733   0.1637   0.1835
## Detection Prevalence   0.2847   0.1942   0.1736   0.1639   0.1835
## Balanced Accuracy      0.9998   0.9987   0.9969   0.9991   0.9993
```

we see an accuracy of 99.82% and a kappa score of 99.77%. . From this we can estimate the out of sample error to be 0.1784% using the accuracy measure, or 0.2256% using the kappa score, both of which are well within the 1% we set for ourselves.

The Testing

Now lets run our model against the test set and see how it fares:

```
    predict_te <- predict(model, test);
    cm_te      <- confusionMatrix(predict_te, answers);
```

Looking at the confusion matrix for the predictions of the test set against the correct outcomes:

```
    cm_te;
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction A B C D E
##          A 7 0 0 0 0
##          B 0 8 0 0 0
##          C 0 0 1 0 0
##          D 0 0 0 1 0
##          E 0 0 0 0 3
##
## Overall Statistics
##
##                Accuracy : 1
##                  95% CI : (0.8316, 1)
##     No Information Rate : 0.4
##     P-Value [Acc > NIR] : 1.1e-08
##
##                   Kappa : 1
##  Mcnemar's Test P-Value : NA
```

```
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity              1.00      1.0     1.00     1.00     1.00
## Specificity              1.00      1.0     1.00     1.00     1.00
## Pos Pred Value           1.00      1.0     1.00     1.00     1.00
## Neg Pred Value           1.00      1.0     1.00     1.00     1.00
## Prevalence               0.35      0.4     0.05     0.05     0.15
## Detection Rate           0.35      0.4     0.05     0.05     0.15
## Detection Prevalence     0.35      0.4     0.05     0.05     0.15
## Balanced Accuracy        1.00      1.0     1.00     1.00     1.00
```

we see our model has performed with 100% accuracy.

The Conclusion

The first model I tried was random forest because it seemed like the best fit for the data, and it performed perfectly - submitted results were 100% correct first time. With some tuning the algorithm itself ran pretty quickly, but without losing accuracy.

The Citation:

Ugulino, W.; Cardador, D.; Vega, K.; Velloso, E.; Milidiu, R.; Fuks, H. Wearable Computing: Accelerometers' Data Classification of Body Postures and Movements. Proceedings of 21st Brazilian Symposium on Artificial Intelligence. Advances in Artificial Intelligence - SBIA 2012. In: Lecture Notes in Computer Science. , pp. 52-61. Curitiba, PR: Springer Berlin / Heidelberg, 2012. ISBN 978-3-642-34458-9. DOI: 10.1007/978-3-642-34459-6_6.

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