

In my analysis regarding the quantified self movement data yielded a relatively simple model that provided fantastic results. I will describe the data transformations implemented, packages and parameters used, as well as expected sample error and cross validation.

Data Transformation

The first step I took was to set all blank vlaues to NA, then remove columns of all NA values, and did so using the below code.

```
train2 = pml.training
train2[pml.training==""]=NA
train = train2[,colSums(is.na(train2))<.8*nrow(train2)]
```

This highlighted any columns that contained 80% NA values and removed them. Due to the large number of observations and predictor variables, I was aggressive in this manner. I also removed the X variable , timestamps (raw, cvtd) as well as new_window and num_window. This left 53 feature variables remaining.

Packages and Parameters

My initial use of the caret package proved frustrating due to very long run times and I looked elsewhere, eventually using randomForest. The number of trees used in the voting was 500. This initial model provided very high accuracy of 0.9972.

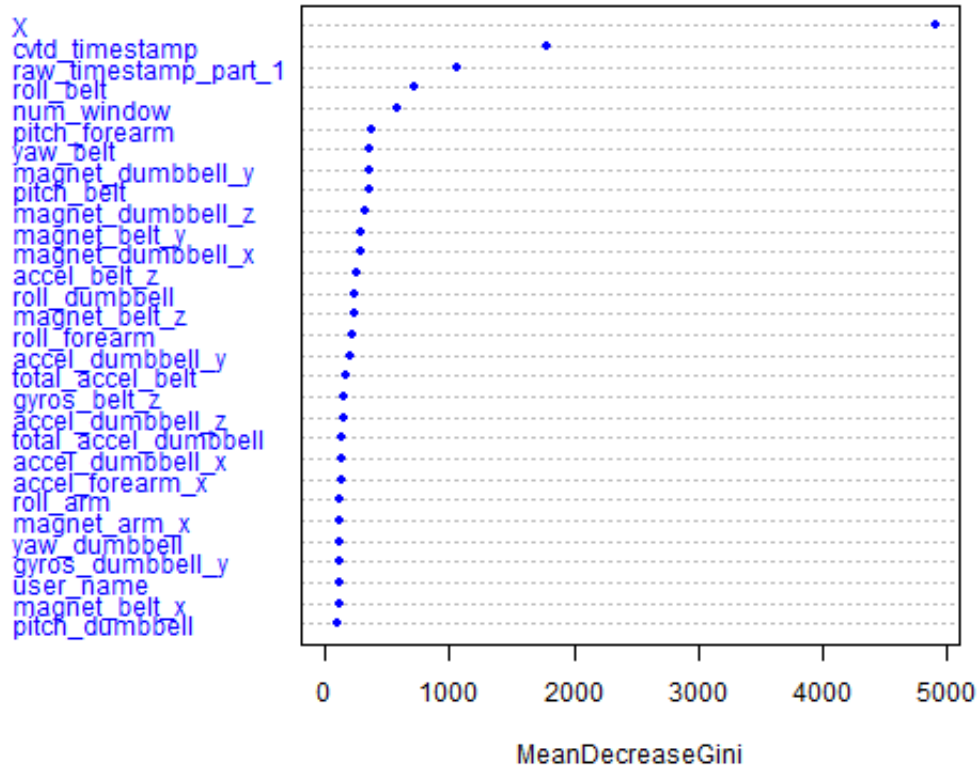
```
## randomForest 4.6-10
## Type rfNews() to see new features/changes/bug fixes.

library("randomForest")
RFfit = randomForest(classe~., data=train, ntree=500)
accuracy = sum(RFfit$predicted==train$classe)/nrow(train)
print(accuracy)

## [1] 0.999949
```

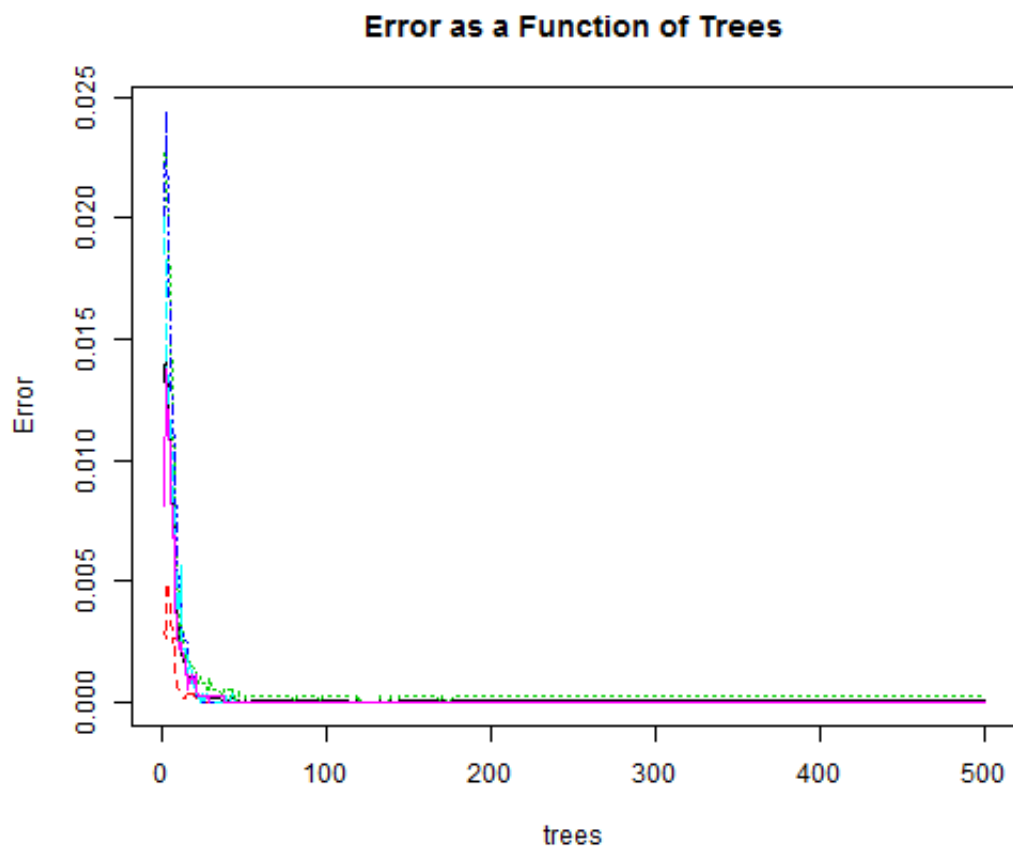
This high accuracy led to concerns of over-fitting. Thus, I looked at the Importance of each predictor as computed by randomForest. I then removed the "less" important variables and refit the model. This made very little difference in accuracy and predicted test results.

Variable Importance as Calculated by randomForest



Expected Sample Error and Cross Validation

Since the in-sample error was very low, I had a small lower bound on the out of sample error of 0.28%.



The package `randomForest` lets you look at average cross validation error with different numbers of predictor variables. I chose a 4-fold cross validation (mainly because computing time).

```
rfcv.fit = rfcv(train[,1:53],train[,54],cv.fold = 4)
rfcv.fit$error.cv
```

##	53	26	13	7	3	1
##	933.6774	775.3896	1069.8067	3034.7335	9426.3456	16634.6613

Thus, `randomForest` provided a great model with minimal tweaking of parameters. (it also correctly predicted all 20 of the test cases!)