Wearable fitness devices collect data that can predict proper weight lifting technique with 99.95% accuracy.

Executive Summary:

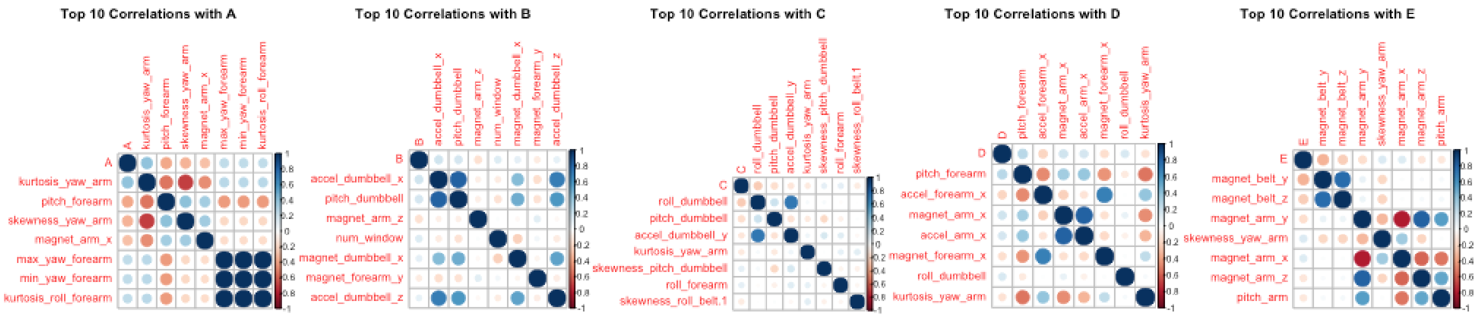
A Gradient Boosting Machine (gbm) is trained using wearable fitness device sensor data to predict whether weight lifting techniques are being performed properly. A trained model is able to achieve 99.95% accuracy predicting the five different outcomes (A = Good Technique; B,C,D,E = Bad Techniques).

Data Preparation Techniques:

1. 19,622 observations of 155 variables were loaded from the source
2. Row names (X), user_name, and all timestamps were removed as predictors to minimize overfitting
3. Training and Testing sets were created using a 70% training random sampling from the overall set
4. To improve efficiency of model generation without losing predictive capabilities, 77 variables with near zero variance were removed from the training set
5. KNN Imputation was used to impute values that were loaded as NA (in cases primarily where values were #DIV/0! and thus columns were converted to factors)
6. Because tree-based methods are a good fit for this multi-class non-linear classification problem, no other monotonic transformations were used

Exploration of Training Data:

Initial data exploration shows many features with significant correlations to each class (A, B, C, D, E):



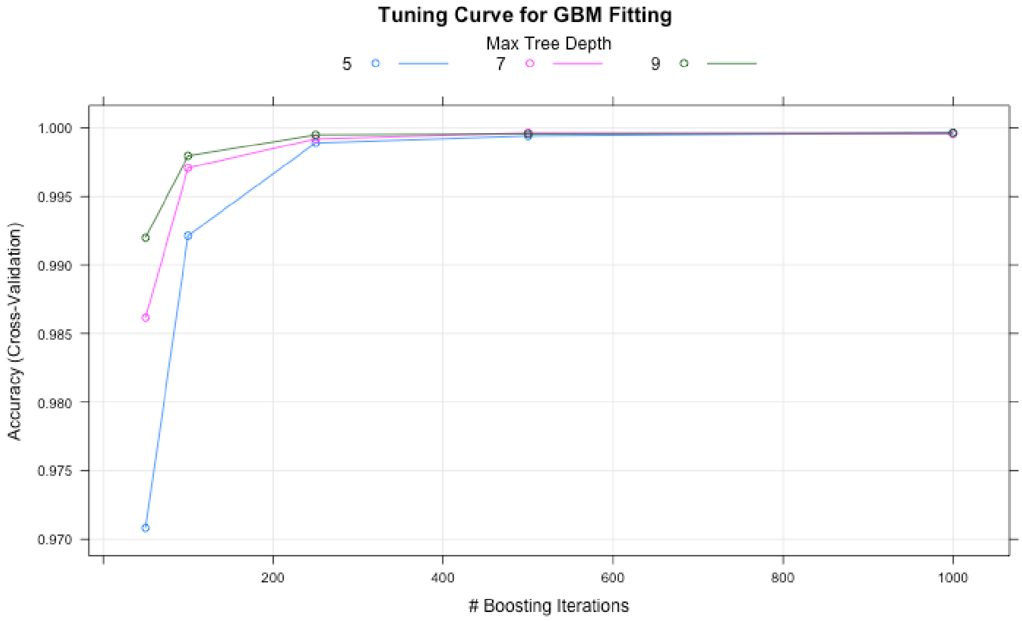
Training the Predictive Algorithms

Three different classification algorithms were tested with varying results: Decision Trees (rpart), Random Forests, and Gradient Boosting Machine (boosted trees). In each trained algorithm, repeated 10-fold cross-validation was performed to minimize overfitting while optimizing tuning parameters for maximum classification accuracy.

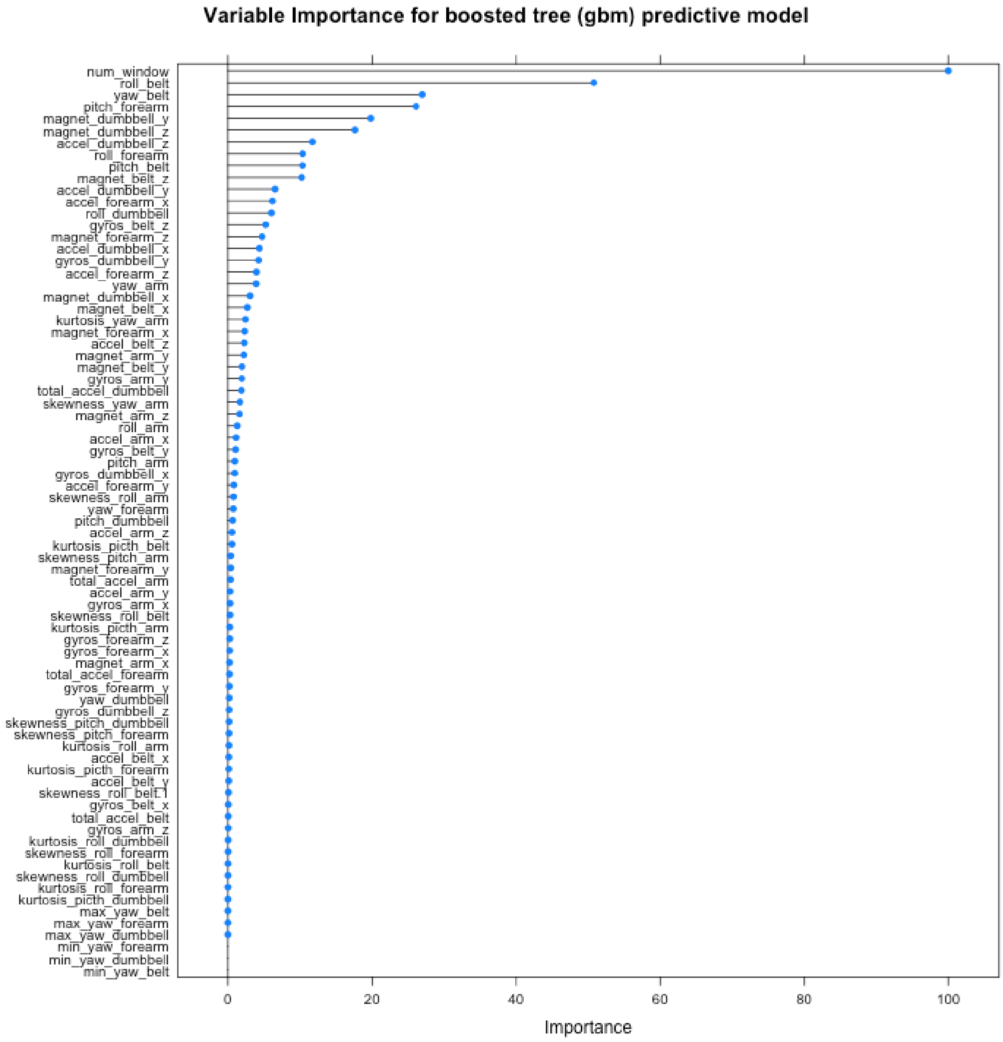
The best performing algorithm was created using **Gradient Boosting Machine (gbm)** package which combines boosting and trees to achieve an outstanding **99.95% overall class prediction accuracy** on test data (or a 0.05% error rate).

Tuning the Algorithm for Maximum Accuracy

Through experimentation, excellent tuning parameters were found using 10-fold cross-validation with 10 repeats. These parameters include 500 trees with an interaction depth of 7 levels, shrinkage of 0.1, and 50 minimum observations in each leaf node.


Tuning Curve for GBM Fitting

Variables with non-zero effects in the final predictive model are plotted below (from most influential to least).


Variable Importance for boosted tree (gbm) predictive model

Results from the Testing Dataset: Confusion Matrix and Summary of Accuracy

```
## Confusion Matrix and Statistics
## 
##           Reference
## Prediction    A    B    C    D    E
##          A 1674    0    0    0    0
##          B    0 1139    0    0    1
##          C    0    0 1026    0    0
##          D    0    0    0  964    2
##          E    0    0    0    0 1079
## 
## Overall Statistics
##                                      
##                Accuracy : 0.9995     
##                  95% CI : (0.9985, 0.9999)
##     No Information Rate : 0.2845     
##     P-Value [Acc > NIR] : < 2.2e-16  
##                                      
##                   Kappa : 0.9994     
##  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   0.9972
## Specificity            1.0000   0.9998   1.0000   0.9996   1.0000
## Pos Pred Value         1.0000   0.9991   1.0000   0.9979   1.0000
## Neg Pred Value         1.0000   1.0000   1.0000   1.0000   0.9994
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2845   0.1935   0.1743   0.1638   0.1833
## Detection Prevalence   0.2845   0.1937   0.1743   0.1641   0.1833
## Balanced Accuracy      1.0000   0.9999   1.0000   0.9998   0.9986
```