Machine Learning Modeling of Selected Weight-lifting Activites

Antonio Rubiera

11/21/2019

Summary of this Analysis

In this analysis, we evaluate the data used by Velloso et al. in their paper "Qualitative Activity Recognition of Weight Lifting Exercises" [ACM SIGCHI 2013]. The data was collected for six young men performing weight-lifting exercises with a light dumbbell (1.25 KG) using five pre-determined sequences (named as the variable 'classe' in the dataset). Sequence A is the correct sequence, and sequences B, C, D, and E are variations of the men performing the weigth-lifting exercise incorrectly. Sequences B, C, D, and E are specific ways to perform the weigth-lifting exercise incorrectly, and this means that the four wrong sequences should be just as separable from each other as they are from A.

We use a specific seed (22) to ensure our data runs are reproducible. We perform exploratory data analysis (EDA), caret model selection, and feature selection in an appendix. The steps relegated to an appendix are as follows:

- Explore the unaggregated training time series data to get a feel for what movements were performed for each sequence, as captured by the classe variable. We plot a small sample of these.
- Explore the aggregated training time series data after selecting only the rows containing these fileds, and removing fields that contain no data, all zeroes and/or all NA values.
- For the aggregated time bin training data, we generate the model accuracy contribution of each feature using the Recursive Feature Elimination (RFE) algorithm. We come up with the features with greater than or equal to 0.75 correlation as features that can be excluded from the classification training algorithms, but none of these fields are found in the test data. Therefore, this selection criteria is not useful in our analysis.
- For the aggregated time bin training data, and using all predictors found in the training data, we apply four models (Decision Tree, Random Forest, Bagged Trees and SVMpoly-short for Support Vector Machines with polynomial kernel) using the caret package to asses the within sample accuracy of predicting the weight-lifting activities using classe as our response variable. We resample from within the training data to obtain confusion matrix results for each caret model.
- For the unaggregated time bin training data, we generate the model accuracy contribution of each feature using the RFE algorithm. We come up with the features with greater than or equal to 0.75 correlation as features that can be excluded from the classification training algorithms. Since some of these fields we want to exclude are found in the test data, we use this knowledge.
- Finally, within the appendix, and for the unaggregated time bin training data, using all predictors found in the training data, we apply the four models we found to have the highest accuracy and kappa measures (Decision Tree, Random Forest, Bagged Trees and SVMpoly), using the caret package to asses the within sample accuracy of predicting the weight-lifting activities using classe as our response variable. We resample here as well from within the training data to obtain confusion matrix results for each caret model.

We estimate in-sample error using the model's accuracy when resampling from within the training data, and out-of-sample error using the model's accuracy when comparing the training data to the test data. All of the percent accuracy numbers quoted in this summary are for a Random Forest model, and we have the same results for three other models (Decision Tree, Bagged Trees and SVMpoly) in the body of the analysis. The estimates for in-sample error using the model's accuracy are in the appendix, and the estimates for out-of-sample error using the model's accuracy are in the three cycles of analysis in the main body of this work.

From the appendix, our in-sample error results for the Random Forest model are:

- 77.5 percent when using only the time-aggregated predictors.
- 84.8 percent when using only the unaggregated predictors, for all fields
- 81.8 percent when using only the unaggregated predictors, for all fields minus the highly correlated fields.

After we perform all of the steps previously outlined and contained here in an appendix, we have four caret models we want to apply on the test data in two cycles:

- In the first cycle, we use all predictors. We obtain predictions for classe for the 20 events in the test data. We estimate that the out of sample error will be close to the in-sample error (approximately 84.8 percent mean accuracy for a Random Forest model using the unaggregate time data). We find the mean accuracy for a Random Forest model to be 79.3 percent using all predictors.
- In the second and cycle, we use only the predictors that have less than 0.75 correlation, based on our cross-validation analysis described in the appendix. We expect the out of sample error will be close to the in-sample error (approximately 81.8 percent mean accuracy for a Random Forest model using the unaggregate time data). We find the mean accuracy for a Random Forest model to be 76.0 percent using only the least-correlated predictors. We expected this accuracy to be higher than the accuracy when using all predictors. In the third and last cycle, We find the mean accuracy for a Random Forest model to be 77.3 using only the top 20 least-correlated predictors. We expected this accuracy to be higher than the accuracy when using all predictors. We subtract one predictor at a time for four additional accuracy measurements and find that the accuracy is 78.8 percent minus one predictor, 76.8 percent minus two predictors, 76.8 percent minus three predictors, and 77.3 percent minus four predictors.

From these three cycles of analysis, our out-of-sample error results for the Random Forest model are:

- 79.3 percent when using only the unaggregated predictors, for all fields
- 76.0 percent when using only the unaggregated predictors, for all fields minus the highly correlated fields. -Within the range between 76.8 percent and 78.8 percent when using only the top 20 unaggregated predictors, and subtracting one field at a time based on the accuracy results of the top 20 model four times.

Analysis Conclusion

We present our conclusion here for the benefit of the Coursera graders. The rest of this analysis has all of the supporting work for this conclusion. We find the in-sample error to be slightly lower than the out-of-sample error. We also find all of the error measurements, using model accuracy as a proxy, to be in the range from the higher 70s percents to the lower 80s percents. Our predictor selection did not change the accuracy results significantly. We attribute this result to a high level of noise in the data, and many missing fields.

```r
library(tidyverse)
library(caret)
library(knitr)
set.seed(22)
```

Time Series (Not Aggregated over Time) Data

The training dataset has two types of data: a time series dataset, and time window measurements of this time series data. Here is the time series data. The measurements in this data for sensors located at the belt, arm (glove), forearm, and dumbbell are:

- The Euler angles (roll, pitch, yaw)
- Gyroscope measurement (x,y,z)
- Magnetometer measurement (x,y,z)
- Acceleration measurement (x,y,z)

```r
training_all <- read.csv("./data/pml-training.csv")
training_all_data <- select(training_all, c("user_name",
                             "raw_timestamp_part_1","raw_timestamp_part_2",
                             "cvtd_timestamp","new_window","num_window","roll_belt",
                             "pitch_belt","yaw_belt","total_accel_belt","gyros_belt_x",
                             "gyros_belt_y","gyros_belt_z","accel_belt_x","accel_belt_y",
                             "accel_belt_z","magnet_belt_x","magnet_belt_y",
                             "magnet_belt_z","roll_arm","pitch_arm","yaw_arm",
                             "total_accel_arm","gyros_arm_x","gyros_arm_y",
                             "gyros_arm_z","accel_arm_x","accel_arm_y","accel_arm_z",
                             "magnet_arm_x","magnet_arm_y","magnet_arm_z","roll_dumbbell",
                             "pitch_dumbbell","yaw_dumbbell","total_accel_dumbbell",
                             "gyros_dumbbell_x","gyros_dumbbell_y","gyros_dumbbell_z",
                             "accel_dumbbell_x","accel_dumbbell_y","accel_dumbbell_z",
                             "roll_forearm","pitch_forearm","yaw_forearm",
                             "total_accel_forearm","gyros_forearm_x",
                             "gyros_forearm_y","gyros_forearm_z","accel_forearm_x",
                             "accel_forearm_y","accel_forearm_z","magnet_forearm_x",
                             "magnet_forearm_y","magnet_forearm_z","classe"))
```

Here are the counts by user_name and classe for the time series data.

```r
kable(table(training_all_data$user_name, training_all_data$classe))
```

	A	B	C	D	E
adelmo	1165	776	750	515	686
carlitos	834	690	493	486	609
charles	899	745	539	642	711
eurico	865	592	489	582	542
jeremy	1177	489	652	522	562
pedro	640	505	499	469	497

Predicting Classe for the Test Data for all Predictors (First Analysis Cycle)

We relegate the explotary data analysis, and running various caret models on resampled training data to an appendix. From this analysis, we determine that four types of models should yield the most accuate results:

- Random Forests (method="rf" in caret train function)
- Decision Trees (method="C5.0" in caret train function)
- Bagged Trees (method="treebag" in caret train function)
- SVM Poly, short for Least Squares Support Vector Machines with Polynomial Kernel (method="svmPoly" in caret train function)

We run on these four models to make our predictions for which classe was performed for the twenty data records collected in the test data. We first need to select the complete observations fields in the test data to match fields in the training data. We save a copy of all of the non-aggregated columns in the training data (training_nonblanks_cv) for a cross-validation analysis enclosed here as an appendix.

```r
training_all_clean <- read.csv("./data/pml-training.csv",
                               na.strings = c("NA","NaN","","#DIV/0!"))
training_nonblanks_clean <- filter(training_all_clean, kurtosis_roll_belt != "")
training_nonblanks_clean <- mutate(training_nonblanks_clean,
                                   rel_time = as.numeric(paste(raw_timestamp_part_1,
                                                               raw_timestamp_part_2,sep=".")))
```

```
training_nonblanks_clean <- select(training_nonblanks_clean,
                c("roll_belt", "pitch_belt", "yaw_belt", "total_accel_belt",
                "gyros_belt_x", "gyros_belt_y", "gyros_belt_z", "accel_belt_x",
                "accel_belt_y", "accel_belt_z", "magnet_belt_x",
                "magnet_belt_y", "magnet_belt_z", "roll_arm", "pitch_arm", "yaw_arm",
                "accel_belt_y", "accel_belt_z", "magnet_belt_x",
                "magnet_arm_y", "magnet_arm_z", "roll_dumbbell", "pitch_dumbbell", "yaw_dumbbell",
                "total_accel_dumbbell", "gyros_dumbbell_x", "gyros_dumbbell_y",
                "gyros_dumbbell_z", "accel_dumbbell_x", "accel_dumbbell_y",
                "accel_dumbbell_z", "magnet_dumbbell_x", "magnet_dumbbell_y",
                "magnet_dumbbell_z", "roll_forearm", "pitch_forearm", "yaw_forearm",
                "total_accel_forearm", "gyros_forearm_x", "gyros_forearm_y", "gyros_forearm_z",
                "accel_forearm_x", "accel_forearm_y",
                "accel_forearm_z", "magnet_forearm_x", "magnet_forearm_y",
                "magnet_forearm_z", "classe"))

training_blanks_cv <- select(training_all, c("roll_belt",
                      "pitch_belt","yaw_belt","total_accel_belt","gyros_belt_x",
                      "gyros_belt_y","gyros_belt_z","accel_belt_x","accel_belt_y",
                      "accel_belt_z","magnet_belt_x","magnet_belt_y",
                      "magnet_belt_z","roll_arm","pitch_arm","yaw_arm",
                      "total_accel_arm","gyros_arm_x","gyros_arm_y",
                      "gyros_arm_z","accel_arm_x","accel_arm_y","accel_arm_z",
                      "magnet_arm_x","magnet_arm_y","magnet_arm_z","roll_dumbbell",
                      "pitch_dumbbell","yaw_dumbbell","total_accel_dumbbell",
                      "gyros_dumbbell_x","gyros_dumbbell_y","gyros_dumbbell_z",
                      "accel_dumbbell_x","accel_dumbbell_y","accel_dumbbell_z",
                      "magnet_dumbbell_x","magnet_dumbbell_y","magnet_dumbbell_z",
                      "roll_forearm","pitch_forearm","yaw_forearm",
                      "total_accel_forearm","gyros_forearm_x",
                      "gyros_forearm_y","gyros_forearm_z","accel_forearm_x",
                      "accel_forearm_y","accel_forearm_z","magnet_forearm_x",
                      "magnet_forearm_y","magnet_forearm_z","classe"))
```

Here is the selection of complete observation fields in the test data.

```
testing_all_clean <- read.csv("./data/pml-testing.csv")
testing_nonblanks_clean <- mutate(testing_all_clean,
                                  rel_time = as.numeric(paste(raw_timestamp_part_1,
                                                              raw_timestamp_part_2,sep=".")))

testing_nonblanks_clean <- select(testing_nonblanks_clean,
                        c("roll_belt", "pitch_belt", "yaw_belt", "total_accel_belt",
                        "gyros_belt_x", "gyros_belt_y", "gyros_belt_z", "accel_belt_x",
                        "accel_belt_y", "accel_belt_z", "magnet_belt_x",
                        "magnet_belt_y", "magnet_belt_z", "roll_arm", "pitch_arm", "yaw_arm",
                        "accel_belt_y", "accel_belt_z", "magnet_belt_x",
                        "magnet_belt_y", "magnet_belt_z", "roll_arm", "pitch_arm", "yaw_arm",
                        "magnet_arm_y", "magnet_arm_z", "roll_dumbbell", "pitch_dumbbell", "yaw_dumbbel
                        "total_accel_dumbbell", "gyros_dumbbell_x", "gyros_dumbbell_y",
                        "gyros_dumbbell_z", "accel_dumbbell_x", "accel_dumbbell_y",
                        "accel_dumbbell_z", "magnet_dumbbell_x", "magnet_dumbbell_y",
                        "magnet_dumbbell_z", "roll_forearm", "pitch_forearm", "yaw_forearm",
```

```
                        "total_accel_forearm", "gyros_forearm_x", "gyros_forearm_y", "gyros_forearm_z",
                        "accel_forearm_x", "accel_forearm_y",
                        "accel_forearm_z", "magnet_forearm_x", "magnet_forearm_y",
                         "magnet_forearm_z", "problem_id"))
```

We setup a resampling control function that we will insert into each model. We use cross validation using a random forest repeated three times.

```
set.seed(22)
controlTS <- rfeControl(functions=rfFuncs, method="repeatedcv", number=3)
```

We find the fields with the highest correlation factor, setting our threshold at 0.75 correlation.

```
set.seed(22)
correlationMatrixTS <- cor(training_nonblanks_clean[,1:44], use="complete.obs")
highlyCorrelatedTS75 <- findCorrelation(correlationMatrixTS, cutoff=0.75)
names(training_nonblanks_clean[,highlyCorrelatedTS75])
```

```
##  [1] "accel_belt_z"      "accel_dumbbell_z"  "roll_belt"
##  [4] "accel_belt_y"      "accel_belt_x"      "total_accel_belt"
##  [7] "magnet_belt_x"     "accel_dumbbell_y"  "magnet_dumbbell_y"
## [10] "magnet_dumbbell_x" "accel_dumbbell_x"  "accel_forearm_y"
## [13] "magnet_arm_z"
```

We use the data with all predictors to perform feature selection using the rfe function in caret. This function performs a simple backwards selection, known as recursive feature elimination (RFE). It finds the model accuracy and kappa for all predictors, and subtracts each least contributing predictor one at a time for the number of predictors we ask (20) out of all predictors.

```
set.seed(22)
resultsTS <- rfe(training_nonblanks_clean[,1:44],
                 training_nonblanks_clean$classe, sizes=c(1:20), rfeControl=controlTS)
print(resultsTS)
```

```
##
## Recursive feature selection
##
## Outer resampling method: Cross-Validated (3 fold, repeated 1 times)
##
## Resampling performance over subset size:
##
##  Variables Accuracy  Kappa AccuracySD  KappaSD Selected
##          1   0.3561 0.1847   0.020044 0.030534
##          2   0.5606 0.4446   0.053030 0.065514
##          3   0.6540 0.5620   0.008748 0.011174
##          4   0.6869 0.6049   0.024353 0.031322
##          5   0.7197 0.6470   0.007576 0.008322
##          6   0.7323 0.6636   0.004374 0.006813
##          7   0.7348 0.6670   0.053030 0.067660
##          8   0.7727 0.7145   0.067335 0.084956
##          9   0.7677 0.7081   0.073580 0.092997
##         10   0.7652 0.7044   0.045455 0.057634
##         11   0.7753 0.7168   0.063081 0.080125        *
##         12   0.7727 0.7137   0.040087 0.050924
##         13   0.7525 0.6882   0.065316 0.082691
##         14   0.7601 0.6979   0.038876 0.049053
```

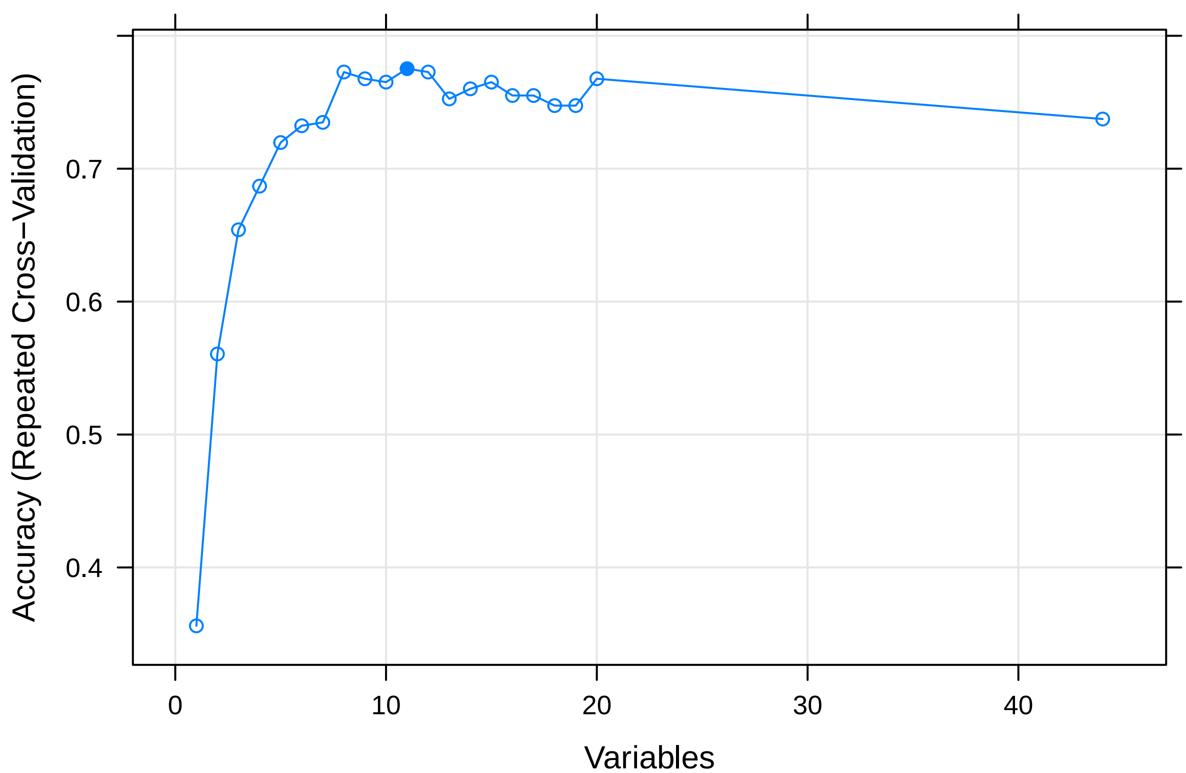
```
##          15   0.7652 0.7039   0.053030 0.066897
##          16   0.7551 0.6914   0.031540 0.040084
##          17   0.7551 0.6912   0.017495 0.022310
##          18   0.7475 0.6815   0.024353 0.030997
##          19   0.7475 0.6815   0.037370 0.047450
##          20   0.7677 0.7072   0.023144 0.029161
##          44   0.7374 0.6687   0.050442 0.063300
##
## The top 5 variables (out of 11):
##    roll_belt, magnet_dumbbell_y, magnet_dumbbell_z, pitch_forearm, magnet_belt_y
```

Here are the most relevant predictors and a plot of the model accuracy (for a Random Forest) as the RFE algorithm subtracts one predictor at a time from the model. By the eight predictor remove, we have model accuracy in the upper 70s percents, where it remains when additional predictors are removed from the model.

```r
set.seed(22)
predictors(resultsTS)
```

```
##  [1] "roll_belt"          "magnet_dumbbell_y" "magnet_dumbbell_z"
##  [4] "pitch_forearm"      "magnet_belt_y"     "roll_dumbbell"
##  [7] "yaw_belt"           "roll_forearm"      "magnet_belt_z"
## [10] "accel_dumbbell_y"  "accel_belt_z"
```

```r
plot(resultsTS, type=c("g", "o"))
```



Running four caret models on all predictors.

We run the training model on the test data for Random Forest (all fields).

```r
set.seed(22)
TcontrolTS <- trainControl(method="repeatedcv", number=10)
modelTSrf <- train(factor(classe) ~ ., data=training_nonblanks_clean,
                   method="rf", preProcess=c("scale","center"),
                   trControl=TcontrolTS, na.action=na.pass)
print(modelTSrf)
```

```
## Random Forest
##
## 396 samples
##  44 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (44), centered (44)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 356, 357, 355, 356, 356, 357, ...
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa
##    2    0.7931707  0.7390597
##   23    0.7731004  0.7146894
##   44    0.7602861  0.6987667
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 2.
```

```r
importanceTSrf <- varImp(modelTSrf, scale=TRUE)
print(importanceTSrf)
```

```
## rf variable importance
##
##   only 20 most important variables shown (out of 44)
##
##                     Overall
## roll_belt            100.00
## magnet_dumbbell_y     73.31
## roll_dumbbell         64.57
## magnet_dumbbell_z     63.37
## pitch_forearm         62.92
## magnet_belt_y         62.33
## yaw_belt              61.41
## accel_dumbbell_y      51.72
## magnet_dumbbell_x     51.36
## magnet_belt_z         50.39
## accel_belt_z          47.09
## pitch_belt            42.66
## roll_forearm          41.65
## accel_dumbbell_x      40.87
## magnet_arm_y          39.33
## gyros_dumbbell_y      38.39
## pitch_dumbbell        37.81
## accel_forearm_x       37.16
## yaw_dumbbell          33.74
## magnet_forearm_x      31.29
```

We predict the classe for the testing data using a Random Forest model.

```
predictrf <- predict(modelTSrf,newdata=testing_nonblanks_clean)
predictrf
```

```
##  [1] A A C A A E D B A A B C A A E E A B A B
## Levels: A B C D E
```

We run the training model on the test data for Decision Trees (all fields).

```
set.seed(22)
modelTSC50 <- train(factor(classe) ~ ., data=training_nonblanks_clean,
                    method="C5.0", preProcess=c("scale","center"),
                    trControl=TcontrolTS, na.action=na.pass)
print(modelTSC50)
```

```
## C5.0
##
## 396 samples
##  44 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (44), centered (44)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 356, 357, 355, 356, 356, 357, ...
## Resampling results across tuning parameters:
##
##   model  winnow  trials  Accuracy   Kappa
##   rules  FALSE    1      0.6690619  0.5832499
##   rules  FALSE   10      0.7574656  0.6951062
##   rules  FALSE   20      0.7774078  0.7198931
##   rules   TRUE    1      0.6845716  0.6011889
##   rules   TRUE   10      0.7525907  0.6883573
##   rules   TRUE   20      0.7829206  0.7267811
##   tree   FALSE    1      0.6517480  0.5622097
##   tree   FALSE   10      0.7400876  0.6733153
##   tree   FALSE   20      0.7577251  0.6946938
##   tree    TRUE    1      0.6867573  0.6053352
##   tree    TRUE   10      0.7652189  0.7049119
##   tree    TRUE   20      0.7601579  0.6976638
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were trials = 20, model = rules
##  and winnow = TRUE.
```

```
importanceTSC50 <- varImp(modelTSC50, scale=TRUE)
print(importanceTSC50)
```

```
## C5.0 variable importance
##
##   only 20 most important variables shown (out of 44)
##
##                    Overall
## pitch_forearm       100.00
## roll_dumbbell       100.00
## magnet_dumbbell_y   100.00
## roll_belt           100.00
```

```
## yaw_arm              100.00
## gyros_belt_x         100.00
## magnet_dumbbell_z     99.49
## accel_dumbbell_x      99.24
## gyros_belt_z          98.48
## roll_forearm          98.23
## yaw_belt              97.22
## total_accel_belt      96.72
## magnet_arm_y          93.94
## gyros_belt_y          92.17
## magnet_belt_z         90.15
## yaw_dumbbell          89.65
## magnet_forearm_y      77.02
## yaw_forearm           60.86
## total_accel_forearm    0.00
## accel_forearm_y        0.00
```

We predict the classe for the testing data using a Decision Trees model.

```
predictC50 <- predict(modelTSC50,newdata=testing_nonblanks_clean)
predictC50
```

```
##  [1] C A B A A E C B A A B C A A E E A D A B
## Levels: A B C D E
```

We run the training model on the test data for Bagged Trees (all fields).

```
set.seed(22)
modelTStreebag <- train(factor(classe) ~ ., data=training_nonblanks_clean,
                   method="treebag", preProcess=c("scale","center"),
                   trControl=TcontrolTS, na.action=na.pass)
print(modelTStreebag)
```

```
## Bagged CART
##
## 396 samples
##  44 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (44), centered (44)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 356, 357, 355, 356, 356, 357, ...
## Resampling results:
##
##   Accuracy   Kappa
##   0.7423984  0.6755765
```

```
importanceTStreebag <- varImp(modelTStreebag, scale=TRUE)
print(importanceTStreebag)
```

```
## treebag variable importance
##
##   only 20 most important variables shown (out of 44)
##
##                     Overall
## roll_belt            100.00
## pitch_forearm         86.47
```

```
## magnet_dumbbell_y   73.72
## yaw_belt            70.86
## roll_dumbbell       66.45
## pitch_belt          63.40
## magnet_belt_y       57.88
## roll_forearm        56.67
## magnet_dumbbell_z   51.86
## accel_dumbbell_y    49.95
## accel_belt_z        47.08
## roll_arm            40.50
## magnet_belt_z       39.14
## total_accel_belt    35.95
## magnet_arm_y        34.59
## gyros_dumbbell_y    34.19
## gyros_belt_z        23.43
## accel_belt_x        23.09
## yaw_dumbbell        22.04
## pitch_dumbbell      21.94
```

We predict the classe for the testing data using a Bagged Trees model.

```
predicttreebag <- predict(modelTStreebag,newdata=testing_nonblanks_clean)
predicttreebag
```

```
##  [1] C A B A A C D B A A B C A A D A A D D B
## Levels: A B C D E
```

We run the training model on the test data for SVM Polynomial Kernel (all fields).

```
set.seed(22)
modelTSsvmPoly <- train(factor(classe) ~ ., data=training_nonblanks_clean,
                   method="svmPoly", preProcess=c("scale","center"),
                   trControl=TcontrolTS, na.action=na.pass)
print(modelTSsvmPoly)
```

```
## Support Vector Machines with Polynomial Kernel
##
## 396 samples
##  44 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (44), centered (44)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 356, 357, 355, 356, 356, 357, ...
## Resampling results across tuning parameters:
##
##   degree  scale  C     Accuracy   Kappa
##   1       0.001  0.25  0.2626626  0.00000000
##   1       0.001  0.50  0.2626626  0.00000000
##   1       0.001  1.00  0.2626626  0.00000000
##   1       0.010  0.25  0.3058677  0.06500791
##   1       0.010  0.50  0.3359991  0.11948811
##   1       0.010  1.00  0.4395372  0.27872584
##   1       0.100  0.25  0.5025657  0.36668396
##   1       0.100  0.50  0.5380206  0.41325553
##   1       0.100  1.00  0.5707802  0.45502812
```

```
##   2       0.001  0.25  0.2626626  0.00000000
##   2       0.001  0.50  0.2626626  0.00000000
##   2       0.001  1.00  0.2956113  0.04894040
##   2       0.010  0.25  0.3537555  0.14436162
##   2       0.010  0.50  0.4753064  0.32689783
##   2       0.010  1.00  0.5205754  0.38958994
##   2       0.100  0.25  0.5992933  0.49411804
##   2       0.100  0.50  0.6091041  0.50693624
##   2       0.100  1.00  0.6268605  0.52979704
##   3       0.001  0.25  0.2626626  0.00000000
##   3       0.001  0.50  0.2852298  0.03234755
##   3       0.001  1.00  0.3259991  0.09430106
##   3       0.010  0.25  0.4778064  0.32878475
##   3       0.010  0.50  0.5383286  0.41127349
##   3       0.010  1.00  0.5989181  0.49071283
##   3       0.100  0.25  0.6212992  0.52300533
##   3       0.100  0.50  0.6188024  0.51953947
##   3       0.100  1.00  0.6213024  0.52254627
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were degree = 2, scale = 0.1 and C = 1.
```

```
importanceTSsvmPoly <- varImp(modelTSsvmPoly, scale=TRUE)
print(importanceTSsvmPoly)
```

```
## ROC curve variable importance
##
##   variables are sorted by maximum importance across the classes
##   only 20 most important variables shown (out of 44)
##
##                          A       B     C     D       E
## pitch_forearm       42.658 100.000 41.00 41.00 100.000
## pitch_dumbbell      43.029  33.469 33.47 75.58  43.029
## roll_dumbbell       46.368  54.198 40.51 73.91  54.198
## magnet_dumbbell_y   68.532  68.532 68.53 71.52  32.182
## magnet_belt_y       10.593  15.791 69.01 10.59  15.791
## magnet_dumbbell_x   58.991  58.991 58.99 66.64  53.058
## roll_belt            9.013  25.320 64.60 18.58  25.320
## magnet_forearm_x    33.265  64.309 35.25 23.76  64.309
## magnet_arm_y        17.261  63.169 55.73 25.17  63.169
## accel_forearm_x     23.724  61.496 24.23 23.72  61.496
## magnet_arm_z        45.204  45.204 60.83 45.20  34.389
## accel_dumbbell_x    37.039  37.039 37.04 59.68  31.164
## magnet_dumbbell_z   54.555  41.396 55.77 25.32  54.555
## magnet_belt_z       11.045  11.045 48.47 11.04   7.939
## pitch_arm           22.288  35.043 46.65 23.84  35.043
## accel_dumbbell_y    34.958  25.509 25.51 45.73  34.958
## accel_belt_z        12.229   7.960 45.03 14.78  12.229
## total_accel_forearm 21.877  21.877 42.92 21.88  19.719
## yaw_dumbbell        24.591   6.839 19.14 42.67  24.591
## accel_dumbbell_z    23.334  23.334 23.33 38.53  12.693
```

We predict the classe for the testing data using a SVM Polynomial Kernel model.

```r
predictsvmPoly <- predict(modelTSsvmPoly,newdata=testing_nonblanks_clean)
predictsvmPoly
```

```
##  [1] A B B C A E D B A A B C A A E E A B D B
## Levels: A B C D E
```

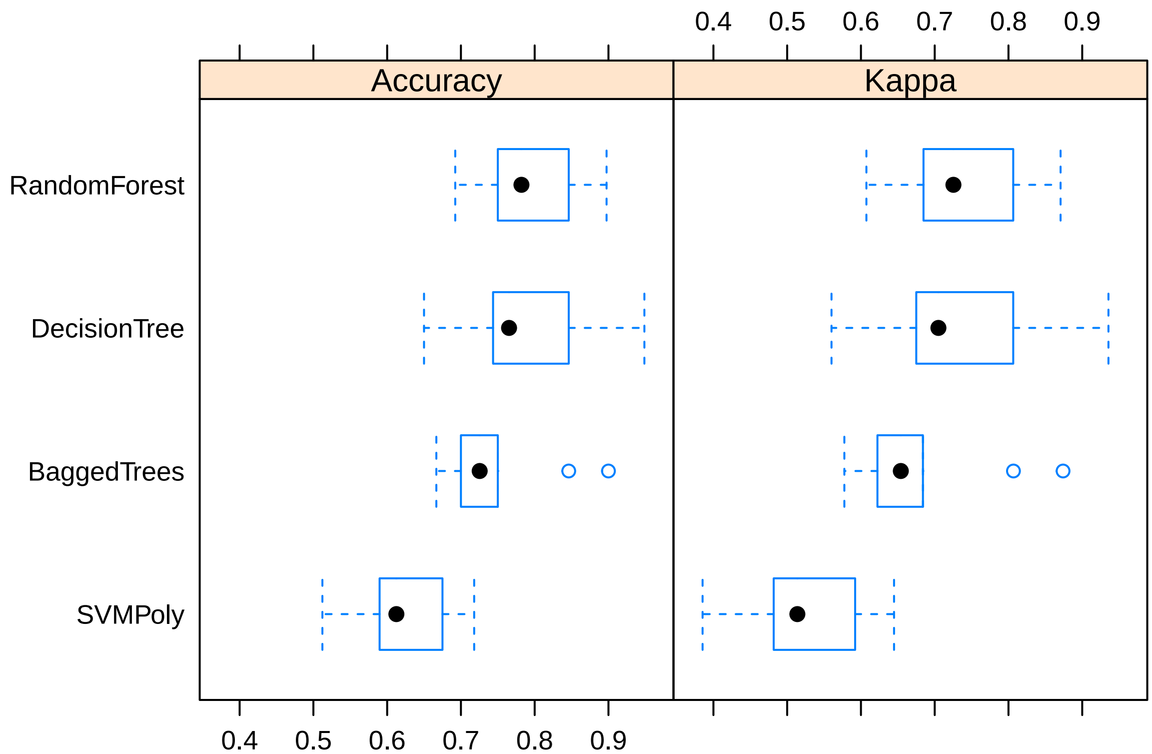
We resample the accuracy and kappa of the four models for all predictors.

```r
set.seed(22)
allModelsall <- resamples(list(SVMPoly=modelTSsvmPoly,
                          DecisionTree=modelTSC50,
                          RandomForest=modelTSrf,
                          BaggedTrees=modelTStreebag
                          ))
summary(allModelsall)
```

```
##
## Call:
## summary.resamples(object = allModelsall)
##
## Models: SVMPoly, DecisionTree, RandomForest, BaggedTrees
## Number of resamples: 10
##
## Accuracy
##                   Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## SVMPoly      0.5121951 0.5923077 0.6125000 0.6268605 0.6729167 0.7179487
## DecisionTree 0.6500000 0.7435897 0.7652439 0.7829206 0.8408654 0.9487179
## RandomForest 0.6923077 0.7500000 0.7820513 0.7931707 0.8408654 0.8974359
## BaggedTrees  0.6666667 0.7000000 0.7254534 0.7423984 0.7483974 0.9000000
##              NA's
## SVMPoly         0
## DecisionTree    0
## RandomForest    0
## BaggedTrees     0
##
## Kappa
##                   Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## SVMPoly      0.3853073 0.4843116 0.5138236 0.5297970 0.5897107 0.6448675
## DecisionTree 0.5600943 0.6758045 0.7050385 0.7267811 0.7999367 0.9355372
## RandomForest 0.6073826 0.6851004 0.7253866 0.7390597 0.7997640 0.8706468
## BaggedTrees  0.5775000 0.6226408 0.6540560 0.6755765 0.6823880 0.8740157
##              NA's
## SVMPoly         0
## DecisionTree    0
## RandomForest    0
## BaggedTrees     0
```

Here is a box plot of the accuracy for the four models we attempted for all predictors.

```r
bwplot(allModelsall)
```



Here are the predictions for the classe of the test data for the four models for all predictors.

```
require(knitr)
predictTableall <- cbind(testing_nonblanks_clean$problem_id,
      predictrf,predictC50,predicttreebag,predictsvmPoly)
kable(predictTableall)
```

	predictrf	predictC50	predicttreebag	predictsvmPoly
1	1	3	3	1
2	1	1	1	2
3	3	2	2	2
4	1	1	1	3
5	1	1	1	1
6	5	5	3	5
7	4	3	4	4
8	2	2	2	2
9	1	1	1	1
10	1	1	1	1
11	2	2	2	2
12	3	3	3	3
13	1	1	1	1
14	1	1	1	1
15	5	5	4	5
16	5	5	1	5
17	1	1	1	1
18	2	4	4	2

	predictrf	predictC50	predicttreebag	predictsvmPoly
19	1	1	4	4
20	2	2	2	2

Predicting Classe for the Test Data for the least correlated Predictors (Second Analysis Cycle)

We have determined the highly correlated fields (in the appendix) and take them our of the classification training for the four models in this analysis.

We run the training model on the test data for Random Forests (minus highly correlated fields).

```
set.seed(22)
modelTSselrf <- train(factor(classe) ~ pitch_belt + yaw_belt + gyros_belt_x +
                  gyros_belt_y + gyros_belt_z +
                  magnet_belt_y + magnet_belt_z + roll_arm + pitch_arm + yaw_arm +
                  accel_belt_y + accel_belt_z + magnet_belt_x +  magnet_arm_y + roll_dumbbell +
                  pitch_dumbbell + yaw_dumbbell + total_accel_dumbbell + gyros_dumbbell_x +
                  gyros_dumbbell_y + gyros_dumbbell_z +  magnet_dumbbell_z + roll_forearm +
                  pitch_forearm + yaw_forearm + total_accel_forearm + gyros_forearm_x +
                  gyros_forearm_y + gyros_forearm_z +  accel_forearm_x + accel_forearm_z +
                  magnet_forearm_x + magnet_forearm_y +
                  magnet_forearm_z, data=training_nonblanks_clean,
                  method="rf", preProcess=c("scale","center"),
                  trControl=TcontrolTS, na.action=na.pass)
print(modelTSselrf)
```

```
## Random Forest
##
## 396 samples
##  34 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (34), centered (34)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 356, 357, 355, 356, 356, 357, ...
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa
##    2    0.7603408  0.6964666
##   18    0.7225844  0.6515497
##   34    0.7122061  0.6385996
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 2.
```

```
importanceTSselrf <- varImp(modelTSselrf, scale=TRUE)
print(importanceTSselrf)
```

```
## rf variable importance
##
##   only 20 most important variables shown (out of 34)
##
##                      Overall
## roll_dumbbell         100.00
```

```
## magnet_belt_y       95.21
## yaw_belt            91.76
## pitch_forearm       82.66
## magnet_dumbbell_z   79.92
## magnet_belt_z       69.77
## accel_belt_z        67.55
## gyros_dumbbell_y    59.91
## pitch_dumbbell      54.61
## pitch_belt          53.98
## yaw_dumbbell        53.58
## magnet_arm_y        48.68
## roll_forearm        46.82
## magnet_forearm_x    44.59
## roll_arm            41.61
## accel_forearm_x     38.18
## accel_forearm_z     35.39
## magnet_forearm_y    35.21
## magnet_belt_x       33.74
## magnet_forearm_z    33.72
```

We predict the classe for the testing data using a Random Forests model.

```
set.seed(22)
predictselrf <- predict(modelTSselrf,newdata=testing_nonblanks_clean)
predictselrf
```

```
##  [1] A A B A A E D B A A B C A A E E A B A B
## Levels: A B C D E
```

We run the training model on the test data for Decision Trees (minus highly correlated fields).

```
set.seed(22)
modelTSselC50 <- train(factor(classe) ~ pitch_belt + yaw_belt + gyros_belt_x + gyros_belt_y + gyros_bel
                   magnet_belt_y + magnet_belt_z + roll_arm + pitch_arm + yaw_arm +
                   accel_belt_y + accel_belt_z + magnet_belt_x +  magnet_arm_y + roll_dumbbell +
                   pitch_dumbbell + yaw_dumbbell + total_accel_dumbbell + gyros_dumbbell_x +
                   gyros_dumbbell_y + gyros_dumbbell_z +  magnet_dumbbell_z + roll_forearm +
                   pitch_forearm + yaw_forearm + total_accel_forearm + gyros_forearm_x +
                   gyros_forearm_y + gyros_forearm_z +  accel_forearm_x + accel_forearm_z +
                   magnet_forearm_x + magnet_forearm_y +
                   magnet_forearm_z, data=training_nonblanks_clean,
                   method="C5.0", preProcess=c("scale","center"),
                   trControl=TcontrolTS, na.action=na.pass)
print(modelTSselC50)
```

```
## C5.0
##
## 396 samples
##  34 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (34), centered (34)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 356, 357, 355, 356, 356, 357, ...
## Resampling results across tuning parameters:
##
```

```
##   model  winnow  trials  Accuracy   Kappa
##   rules  FALSE    1      0.5962258  0.4901181
##   rules  FALSE   10      0.6970747  0.6191215
##   rules  FALSE   20      0.7020685  0.6252653
##   rules   TRUE    1      0.5884021  0.4807725
##   rules   TRUE   10      0.6821873  0.6007882
##   rules   TRUE   20      0.6923218  0.6129405
##   tree   FALSE    1      0.5890400  0.4834259
##   tree   FALSE   10      0.6899406  0.6099756
##   tree   FALSE   20      0.6920654  0.6131378
##   tree    TRUE    1      0.6234146  0.5254442
##   tree    TRUE   10      0.6716198  0.5862588
##   tree    TRUE   20      0.6944434  0.6150183
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were trials = 20, model = rules
##  and winnow = FALSE.
```

```
importanceTSselC50 <- varImp(modelTSselC50, scale=TRUE)
print(importanceTSselC50)
```

```
## C5.0 variable importance
##
##   only 20 most important variables shown (out of 34)
##
##                      Overall
## magnet_dumbbell_z     100.00
## accel_belt_z          100.00
## magnet_belt_y         100.00
## yaw_arm               100.00
## pitch_belt            100.00
## gyros_belt_z          100.00
## gyros_belt_x          100.00
## gyros_belt_y           98.58
## yaw_dumbbell           98.58
## gyros_dumbbell_y       98.22
## pitch_forearm          97.86
## roll_dumbbell          97.51
## magnet_belt_z          96.43
## yaw_belt               94.66
## roll_forearm           93.24
## accel_belt_y           91.81
## magnet_arm_y           90.04
## gyros_dumbbell_x       84.34
## magnet_forearm_x       81.85
## total_accel_dumbbell   79.72
```

We predict the classe for the testing data using a Decision Trees model.

```
set.seed(22)
predictselC50 <- predict(modelTSselC50,newdata=testing_nonblanks_clean)
predictselC50
```

```
##  [1] A A A A A E D B A A B C A A E E A B A B
## Levels: A B C D E
```

We run the training model on the test data for Bagged Trees (minus highly correlated fields).

```
set.seed(22)
modelTSseltreebag <- train(factor(classe) ~ pitch_belt + yaw_belt +
                       gyros_belt_x + gyros_belt_y + gyros_belt_z +
                       magnet_belt_y + magnet_belt_z + roll_arm + pitch_arm + yaw_arm +
                       accel_belt_y + accel_belt_z + magnet_belt_x +  magnet_arm_y + roll_dumbbell +
                       pitch_dumbbell + yaw_dumbbell + total_accel_dumbbell + gyros_dumbbell_x +
                       gyros_dumbbell_y + gyros_dumbbell_z +  magnet_dumbbell_z + roll_forearm +
                       pitch_forearm + yaw_forearm + total_accel_forearm + gyros_forearm_x +
                       gyros_forearm_y + gyros_forearm_z +  accel_forearm_x + accel_forearm_z +
                       magnet_forearm_x + magnet_forearm_y +
                       magnet_forearm_z, data=training_nonblanks_clean,
                       method="treebag", preProcess=c("scale","center"),
                       trControl=TcontrolTS, na.action=na.pass)
print(modelTSseltreebag)
```

```
## Bagged CART
##
## 396 samples
##  34 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (34), centered (34)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 356, 357, 355, 356, 356, 357, ...
## Resampling results:
##
##   Accuracy   Kappa
##   0.7045716  0.6285172
```

```
importanceTSseltreebag <- varImp(modelTSseltreebag, scale=TRUE)
print(importanceTSseltreebag)
```

```
## treebag variable importance
##
##   only 20 most important variables shown (out of 34)
##
##                   Overall
## pitch_forearm      100.00
## yaw_belt            89.42
## magnet_belt_y       84.73
## magnet_belt_z       74.85
## roll_dumbbell       71.01
## gyros_belt_z        62.37
## magnet_dumbbell_z   59.57
## pitch_belt          56.76
## magnet_arm_y        45.72
## accel_belt_z        45.05
## roll_arm            44.30
## gyros_dumbbell_y    41.28
## gyros_belt_x        40.31
## roll_forearm        36.63
## yaw_arm             31.34
## pitch_dumbbell      30.45
```

```
## pitch_arm           26.04
## gyros_dumbbell_x    21.51
## accel_forearm_z     20.69
## yaw_dumbbell        20.36
```

We predict the classe for the testing data using a Bagged Trees model.

```r
set.seed(22)
predictseltreebag <- predict(modelTSseltreebag,newdata=testing_nonblanks_clean)
predictseltreebag
```

```
##  [1] D A B A A E C B A A B C B A E B A D A B
## Levels: A B C D E
```

We run the training model on the test data for SVM Polynomial Kernel (minus highly correlated fields).

```r
set.seed(22)
modelTSselsvmPoly <- train(factor(classe) ~ pitch_belt + yaw_belt + gyros_belt_x +
                       gyros_belt_y + gyros_belt_z +
                       magnet_belt_y + magnet_belt_z + roll_arm + pitch_arm + yaw_arm +
                       accel_belt_y + accel_belt_z + magnet_belt_x +  magnet_arm_y + roll_dumbbell +
                       pitch_dumbbell + yaw_dumbbell + total_accel_dumbbell + gyros_dumbbell_x +
                       gyros_dumbbell_y + gyros_dumbbell_z +  magnet_dumbbell_z + roll_forearm +
                       pitch_forearm + yaw_forearm + total_accel_forearm + gyros_forearm_x +
                       gyros_forearm_y + gyros_forearm_z +  accel_forearm_x + accel_forearm_z +
                       magnet_forearm_x + magnet_forearm_y +
                       magnet_forearm_z, data=training_nonblanks_clean,
                       method="svmPoly", preProcess=c("scale","center"),
                       trControl=TcontrolTS, na.action=na.pass)
print(modelTSselsvmPoly)
```

```
## Support Vector Machines with Polynomial Kernel
##
## 396 samples
##  34 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (34), centered (34)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 356, 357, 355, 356, 356, 357, ...
## Resampling results across tuning parameters:
##
##   degree  scale  C     Accuracy   Kappa
##   1       0.001  0.25  0.2626626  0.00000000
##   1       0.001  0.50  0.2626626  0.00000000
##   1       0.001  1.00  0.2626626  0.00000000
##   1       0.010  0.25  0.3056785  0.06237564
##   1       0.010  0.50  0.3361273  0.11089672
##   1       0.010  1.00  0.3893355  0.21282607
##   1       0.100  0.25  0.4699922  0.32675164
##   1       0.100  0.50  0.5103862  0.37834095
##   1       0.100  1.00  0.5228252  0.39382569
##   2       0.001  0.25  0.2626626  0.00000000
##   2       0.001  0.50  0.2626626  0.00000000
##   2       0.001  1.00  0.2852298  0.03278183
##   2       0.010  0.25  0.3435663  0.12197521
```

```
## 2 0.010 0.50 0.4169028 0.25061128
## 2 0.010 1.00 0.4752455 0.33147554
## 2 0.100 0.25 0.6091714 0.50683536
## 2 0.100 0.50 0.6142964 0.51351176
## 2 0.100 1.00 0.6141714 0.51370029
## 3 0.001 0.25 0.2626626 0.00000000
## 3 0.001 0.50 0.2651626 0.00385914
## 3 0.001 1.00 0.3108068 0.07036584
## 3 0.010 0.25 0.3943355 0.21602204
## 3 0.010 0.50 0.4852455 0.34440715
## 3 0.010 1.00 0.5281395 0.39909232
## 3 0.100 0.25 0.6267480 0.53028108
## 3 0.100 0.50 0.6263024 0.52950230
## 3 0.100 1.00 0.6238024 0.52645449
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were degree = 3, scale = 0.1 and C
##  = 0.25.
```

```
importanceTSselsvmPoly <- varImp(modelTSselsvmPoly, scale=TRUE)
print(importanceTSselsvmPoly)
```

```
## ROC curve variable importance
##
##   variables are sorted by maximum importance across the classes
##   only 20 most important variables shown (out of 34)
##
##                          A       B      C      D       E
## pitch_forearm        42.66 100.000 40.999 40.999 100.000
## pitch_dumbbell       43.03  33.469 33.469 75.576  43.029
## roll_dumbbell        46.37  54.198 40.506 73.906  54.198
## magnet_belt_y        10.59  15.791 69.015 10.593  15.791
## magnet_forearm_x     33.26  64.309 35.247 23.765  64.309
## magnet_arm_y         17.26  63.169 55.726 25.171  63.169
## accel_forearm_x      23.72  61.496 24.227 23.724  61.496
## magnet_dumbbell_z    54.56  41.396 55.767 25.324  54.555
## magnet_belt_z        11.04  11.045 48.474 11.045   7.939
## pitch_arm            22.29  35.043 46.651 23.841  35.043
## accel_belt_z         12.23   7.960 45.031 14.780  12.229
## total_accel_forearm  21.88  21.877 42.924 21.877  19.719
## yaw_dumbbell         24.59   6.839 19.143 42.673  24.591
## magnet_forearm_y     28.87  37.444 28.873 36.860  37.444
## roll_arm             36.28  36.280 36.280 36.280  18.119
## roll_forearm         33.17  18.738 18.738 18.738  33.172
## yaw_arm              32.36  32.361 32.361 32.361  24.181
## magnet_forearm_z     30.57  17.440  8.994 25.665  30.574
## yaw_belt             26.86  26.863 26.863 30.026   8.323
## gyros_forearm_y      29.62  14.458  9.239  9.239  29.624
```

We predict the classe for the testing data using a SVM Polynomial Kernel model.

```
set.seed(22)
predictselsvmPoly <- predict(modelTSselsvmPoly,newdata=testing_nonblanks_clean)
predictselsvmPoly
```

```
##  [1] A B B C A B D B A A B C A A E E A B A B
```

```
## Levels: A B C D E
```

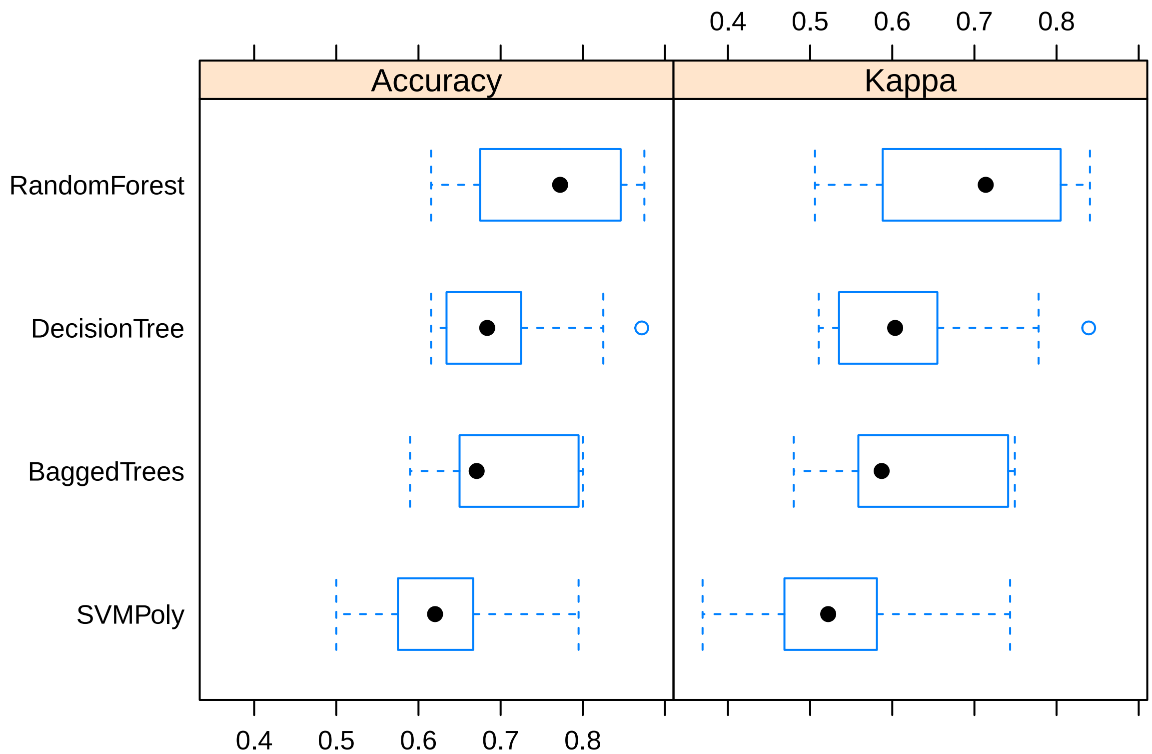
We resample the accuracy and kappa of the four models for the least correlated predictors.

```r
set.seed(22)
allModelssel <- resamples(list(SVMPoly=modelTSselsvmPoly,
                           DecisionTree=modelTSselC50,
                           RandomForest=modelTSselrf,
                           BaggedTrees=modelTSseltreebag
                           ))
summary(allModelssel)
```

```
##
## Call:
## summary.resamples(object = allModelssel)
##
## Models: SVMPoly, DecisionTree, RandomForest, BaggedTrees
## Number of resamples: 10
##
## Accuracy
##                   Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## SVMPoly      0.5000000 0.5812500 0.6201923 0.6267480 0.6585366 0.7948718
## DecisionTree 0.6153846 0.6422764 0.6836538 0.7020685 0.7187500 0.8717949
## RandomForest 0.6153846 0.6857372 0.7724359 0.7603408 0.8397436 0.8750000
## BaggedTrees  0.5897436 0.6521341 0.6708333 0.7045716 0.7899038 0.8000000
##              NA's
## SVMPoly         0
## DecisionTree    0
## RandomForest    0
## BaggedTrees     0
##
## Kappa
##                   Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## SVMPoly      0.3690852 0.4749802 0.5219717 0.5302811 0.5699656 0.7434211
## DecisionTree 0.5104603 0.5469536 0.6034870 0.6252653 0.6479364 0.8391089
## RandomForest 0.5059122 0.6017619 0.7137888 0.6964666 0.7974381 0.8406375
## BaggedTrees  0.4800000 0.5627344 0.5871161 0.6285172 0.7346629 0.7492163
##              NA's
## SVMPoly         0
## DecisionTree    0
## RandomForest    0
## BaggedTrees     0
```

Here is a box plot of the accuracy for the four models we attempted for the least correlated predictors.

```r
bwplot(allModelssel)
```



Here are the predictions for the classe of the test data for the four models for the least correlated predictors.

```
require(knitr)
predictTable <- cbind(testing_nonblanks_clean$problem_id,
          predictselrf,predictselC50,predictseltreebag,predictselsvmPoly)
kable(predictTable)
```

	predictselrf	predictselC50	predictseltreebag	predictselsvmPoly
1	1	1	4	1
2	1	1	1	2
3	2	1	2	2
4	1	1	1	3
5	1	1	1	1
6	5	5	5	2
7	4	4	3	4
8	2	2	2	2
9	1	1	1	1
10	1	1	1	1
11	2	2	2	2
12	3	3	3	3
13	1	1	2	1
14	1	1	1	1
15	5	5	5	5
16	5	5	2	5
17	1	1	1	1
18	2	2	4	2

	predictselrf	predictselC50	predictseltreebag	predictselsvmPoly
19	1	1	1	1
20	2	2	2	2

Predicting Classe for the Test Data for the top 20 and fewer Predictors (Third Analysis Cycle)

We run the training model on the test data for Random Forest (top 20 least correlated fields).

```
set.seed(22)
modelTSselrftop20 <- train(factor(classe) ~ roll_dumbbell + magnet_belt_y +
                              yaw_belt + pitch_forearm + magnet_dumbbell_z +
                              magnet_belt_z + accel_belt_z + gyros_dumbbell_y +
                              pitch_dumbbell  + pitch_belt + yaw_dumbbell + magnet_arm_y +
                              accel_forearm_x  + accel_forearm_z  + magnet_forearm_y  +
                              data=training_nonblanks_clean,
                              method="rf", preProcess=c("scale","center"),
                              trControl=TcontrolTS, na.action=na.pass)
importanceTSselrftop20 <- varImp(modelTSselrftop20, scale=TRUE)
print(importanceTSselrftop20)
```

```
## rf variable importance
##
##                   Overall
## magnet_dumbbell_z 100.000
## yaw_belt           97.557
## roll_dumbbell      97.212
## magnet_belt_y      96.452
## pitch_forearm      81.557
## magnet_belt_z      74.519
## accel_belt_z       68.152
## pitch_belt         58.132
## yaw_dumbbell       43.605
## gyros_dumbbell_y   42.781
## roll_forearm       42.063
## pitch_dumbbell     30.228
## magnet_arm_y       27.365
## roll_arm           23.995
## accel_forearm_x    13.107
## magnet_forearm_x   13.030
## magnet_forearm_z   10.435
## accel_forearm_z     7.662
## magnet_belt_x       5.096
## magnet_forearm_y    0.000
```

```
predictselrftop20 <- predict(modelTSselrftop20,newdata=testing_nonblanks_clean)
predictselrftop20
```

```
##  [1] A A B A A E D B A A B C B A E E A B A B
## Levels: A B C D E
```

First subtraction: stepwise, we are getting rid of predictors one by one; magnet_forearm_y, with a 0.000 percent contribution to the accuracy.

```r
set.seed(22)
modelTSselrfminus1 <- train(factor(classe) ~ roll_dumbbell + magnet_belt_y +
                             yaw_belt + pitch_forearm + magnet_dumbbell_z +
                             magnet_belt_z + accel_belt_z + gyros_dumbbell_y +
                             pitch_dumbbell  + pitch_belt + yaw_dumbbell + magnet_arm_y +
                             accel_forearm_x  + accel_forearm_z  +
                   data=training_nonblanks_clean,
                   method="rf", preProcess=c("scale","center"),
                   trControl=TcontrolTS, na.action=na.pass)
importanceTSselrfminus1 <- varImp(modelTSselrfminus1, scale=TRUE)
print(importanceTSselrfminus1)
```

```
## rf variable importance
##
##                    Overall
## yaw_belt           100.000
## pitch_forearm       89.795
## roll_dumbbell       87.423
## magnet_dumbbell_z   84.304
## magnet_belt_y       82.467
## magnet_belt_z       71.185
## accel_belt_z        62.075
## pitch_belt          45.859
## gyros_dumbbell_y    43.176
## yaw_dumbbell        34.095
## magnet_arm_y        28.918
## roll_forearm        25.489
## pitch_dumbbell      23.673
## roll_arm            18.224
## accel_forearm_x      9.664
## magnet_forearm_z     7.408
## accel_forearm_z      2.806
## magnet_forearm_x     2.555
## magnet_belt_x        0.000
```

```r
predictselrfminus1 <- predict(modelTSselrfminus1,newdata=testing_nonblanks_clean)
predictselrfminus1
```

```
##  [1] A A B A A E D B A A B C A A E E A B A B
## Levels: A B C D E
```

Second subtraction: stepwise, we are getting rid of predictors one by one; accel_forearm_z, with a 4.376 percent importance to the accuracy.

```r
set.seed(22)
modelTSselrfminus2 <- train(factor(classe) ~ roll_dumbbell + magnet_belt_y +
                             yaw_belt + pitch_forearm + magnet_dumbbell_z +
                             magnet_belt_z + accel_belt_z + gyros_dumbbell_y +
                             pitch_dumbbell  + pitch_belt + yaw_dumbbell + magnet_arm_y +
                             accel_forearm_x  + magnet_belt_x  + magnet_forearm_z ,
                   data=training_nonblanks_clean,
                   method="rf", preProcess=c("scale","center"),
                   trControl=TcontrolTS, na.action=na.pass)
importanceTSselrfminus2 <- varImp(modelTSselrfminus2, scale=TRUE)
print(importanceTSselrfminus2)
```

```
## rf variable importance
##
##                    Overall
## yaw_belt           100.000
## magnet_belt_y       86.918
## magnet_dumbbell_z   81.400
## roll_dumbbell       80.387
## pitch_forearm       72.762
## magnet_belt_z       65.651
## pitch_belt          47.921
## gyros_dumbbell_y    41.967
## yaw_dumbbell        41.868
## accel_belt_z        40.981
## pitch_dumbbell      35.073
## roll_forearm        30.838
## roll_arm            19.465
## magnet_arm_y        17.216
## magnet_forearm_x    11.331
## magnet_forearm_z     7.417
## accel_forearm_x      4.640
## magnet_belt_x        0.000
```

```r
predictselrfminus2 <- predict(modelTSselrfminus2,newdata=testing_nonblanks_clean)
predictselrfminus2
```

```
##  [1] A A B A A E D B A A B C B A E E A B A B
## Levels: A B C D E
```

Third subtraction: stepwise, we are getting rid of predictors one by one; accel_forearm_z, with a 4.376 percent importance to the accuracy.

Stepwise getting rid of predictors one by one: magnet_belt_x 6.859 3

```r
set.seed(22)
modelTSselrfminus3 <- train(factor(classe) ~ roll_dumbbell + magnet_belt_y +
                             yaw_belt + pitch_forearm + magnet_dumbbell_z +
                             magnet_belt_z + accel_belt_z + gyros_dumbbell_y +
                             pitch_dumbbell  + pitch_belt + yaw_dumbbell + magnet_arm_y +
                             accel_forearm_x  +  magnet_forearm_z,
                  data=training_nonblanks_clean,
                  method="rf", preProcess=c("scale","center"),
                  trControl=TcontrolTS, na.action=na.pass)
importanceTSselrfminus3 <- varImp(modelTSselrfminus3, scale=TRUE)
print(importanceTSselrfminus3)
```

```
## rf variable importance
##
##                    Overall
## roll_dumbbell      100.000
## pitch_forearm       93.252
## yaw_belt            91.054
## magnet_dumbbell_z   84.720
## magnet_belt_y       80.145
## magnet_belt_z       71.345
## accel_belt_z        65.831
## pitch_belt          42.531
```

```
## gyros_dumbbell_y   41.001
## yaw_dumbbell       32.930
## magnet_arm_y       29.719
## roll_forearm       26.266
## pitch_dumbbell     20.464
## roll_arm            8.924
## magnet_forearm_z    7.284
## magnet_forearm_x    6.584
## accel_forearm_x     0.000
```

```
predictselrfminus3 <- predict(modelTSselrfminus3,newdata=testing_nonblanks_clean)
predictselrfminus3
```

```
##  [1] C A B A A E D B A A B C A A E E A B A B
## Levels: A B C D E
```

Fourth, and final subtraction: stepwise, we are getting rid of predictors one by one; magnet_forearm_z, with a 10.501 percent importance to the accuracy.

```
set.seed(22)
modelTSselrfminus4 <- train(factor(classe) ~ roll_dumbbell + magnet_belt_y +
                             yaw_belt + pitch_forearm + magnet_dumbbell_z +
                             magnet_belt_z + accel_belt_z + gyros_dumbbell_y +
                             pitch_dumbbell  + pitch_belt + yaw_dumbbell + magnet_arm_y +
                             accel_forearm_x,
                  data=training_nonblanks_clean,
                  method="rf", preProcess=c("scale","center"),
                  trControl=TcontrolTS, na.action=na.pass)
importanceTSselrfminus4 <- varImp(modelTSselrfminus4, scale=TRUE)
print(importanceTSselrfminus4)
```

```
## rf variable importance
##
##                   Overall
## yaw_belt           100.00
## magnet_dumbbell_z   90.93
## roll_dumbbell       84.44
## pitch_forearm       81.48
## magnet_belt_y       78.34
## accel_belt_z        59.86
## pitch_belt          55.52
## magnet_belt_z       54.97
## gyros_dumbbell_y    38.90
## roll_forearm        34.97
## yaw_dumbbell        31.54
## magnet_arm_y        31.25
## pitch_dumbbell      24.15
## roll_arm            14.75
## accel_forearm_x     10.63
## magnet_forearm_x     0.00
```

```
predictselrfminus4 <- predict(modelTSselrfminus4,newdata=testing_nonblanks_clean)
predictselrfminus4
```

```
##  [1] A A B A A E D B A A B C A A E E A B A B
## Levels: A B C D E
```

Here are the predictions for the classe of the test data for the four models for the top 20 predictors and four stepwise subtractions.

```r
require(knitr)
predictTable2 <- cbind(testing_nonblanks_clean$problem_id,predictselrftop20,
      predictselrfminus1,predictselrfminus2,predictselrfminus3,
      predictselrfminus4)
kable(predictTable2)
```

	predictselrftop20	predictselrfminus1	predictselrfminus2	predictselrfminus3	predictselrfminus4
1	1	1	1	3	1
2	1	1	1	1	1
3	2	2	2	2	2
4	1	1	1	1	1
5	1	1	1	1	1
6	5	5	5	5	5
7	4	4	4	4	4
8	2	2	2	2	2
9	1	1	1	1	1
10	1	1	1	1	1
11	2	2	2	2	2
12	3	3	3	3	3
13	2	1	2	1	1
14	1	1	1	1	1
15	5	5	5	5	5
16	5	5	5	5	5
17	1	1	1	1	1
18	2	2	2	2	2
19	1	1	1	1	1
20	2	2	2	2	2

We resample the accuracy and kappa for the top 20 predictors and four stepwise subtractions.

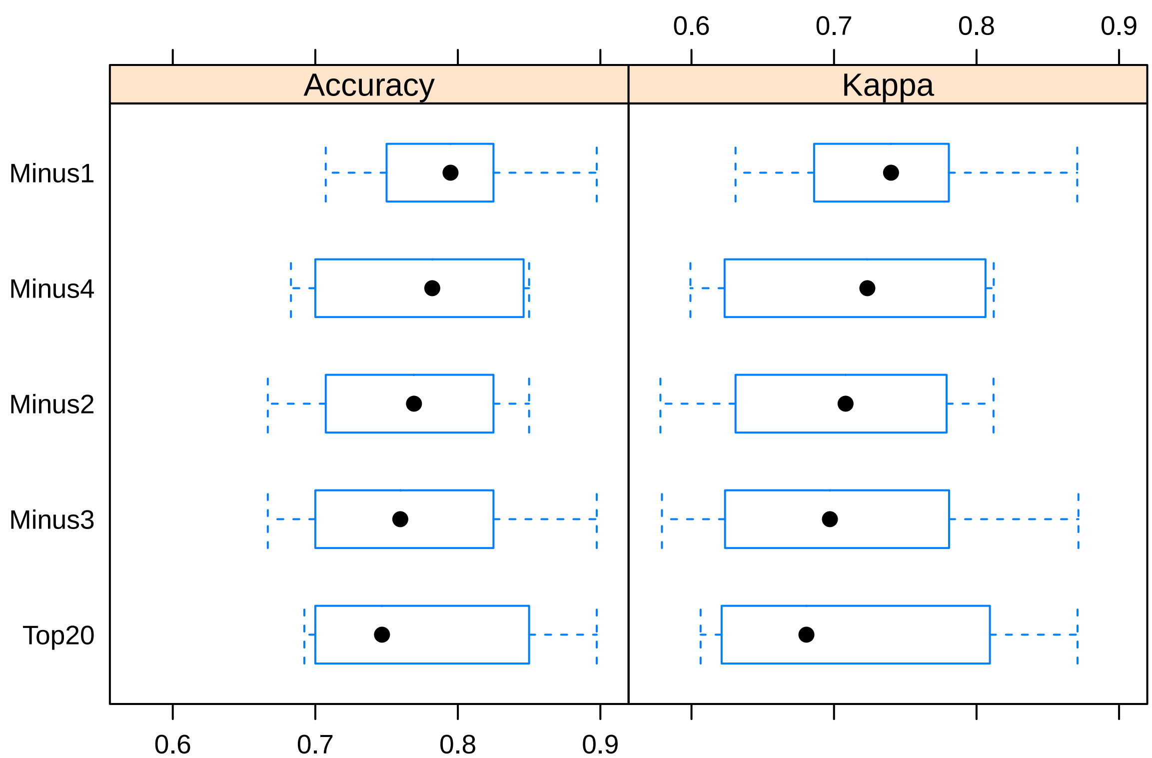
```r
set.seed(22)
allModelsselminus <- resamples(list(Top20=modelTSselrftop20,
                          Minus1=modelTSselrfminus1,
                          Minus2=modelTSselrfminus2,
                          Minus3=modelTSselrfminus3,
                          Minus4=modelTSselrfminus4
                          ))
summary(allModelsselminus)
```

```
##
## Call:
## summary.resamples(object = allModelsselminus)
##
## Models: Top20, Minus1, Minus2, Minus3, Minus4
## Number of resamples: 10
##
## Accuracy
##             Min.   1st Qu.    Median      Mean   3rd Qu.      Max. NA's
## Top20  0.6923077 0.7079268 0.7467949 0.7727861 0.8426282 0.8974359    0
## Minus1 0.7073171 0.7500000 0.7948718 0.7882317 0.8174679 0.8974359    0
## Minus2 0.6666667 0.7117378 0.7692308 0.7679112 0.8238782 0.8500000    0
```

```
## Minus3 0.6666667 0.7108974 0.7596154 0.7681004 0.8187500 0.8974359    0
## Minus4 0.6829268 0.7125000 0.7820513 0.7731645 0.8346154 0.8500000    0
##
## Kappa
##             Min.   1st Qu.    Median      Mean   3rd Qu.      Max. NA's
## Top20  0.6063919 0.6314705 0.6806494 0.7131094 0.8007175 0.8708609    0
## Minus1 0.6309077 0.6861513 0.7399971 0.7329437 0.7709604 0.8706468    0
## Minus2 0.5782030 0.6369739 0.7081077 0.7075694 0.7779423 0.8119122    0
## Minus3 0.5792531 0.6360571 0.6971267 0.7075566 0.7722108 0.8714992    0
## Minus4 0.5992481 0.6389325 0.7233988 0.7137070 0.7913773 0.8120595    0
```

Here is a box plot of the accuracy for the top 20 predictors and four stepwise subtractions.

```
bwplot(allModelsselminus)
```



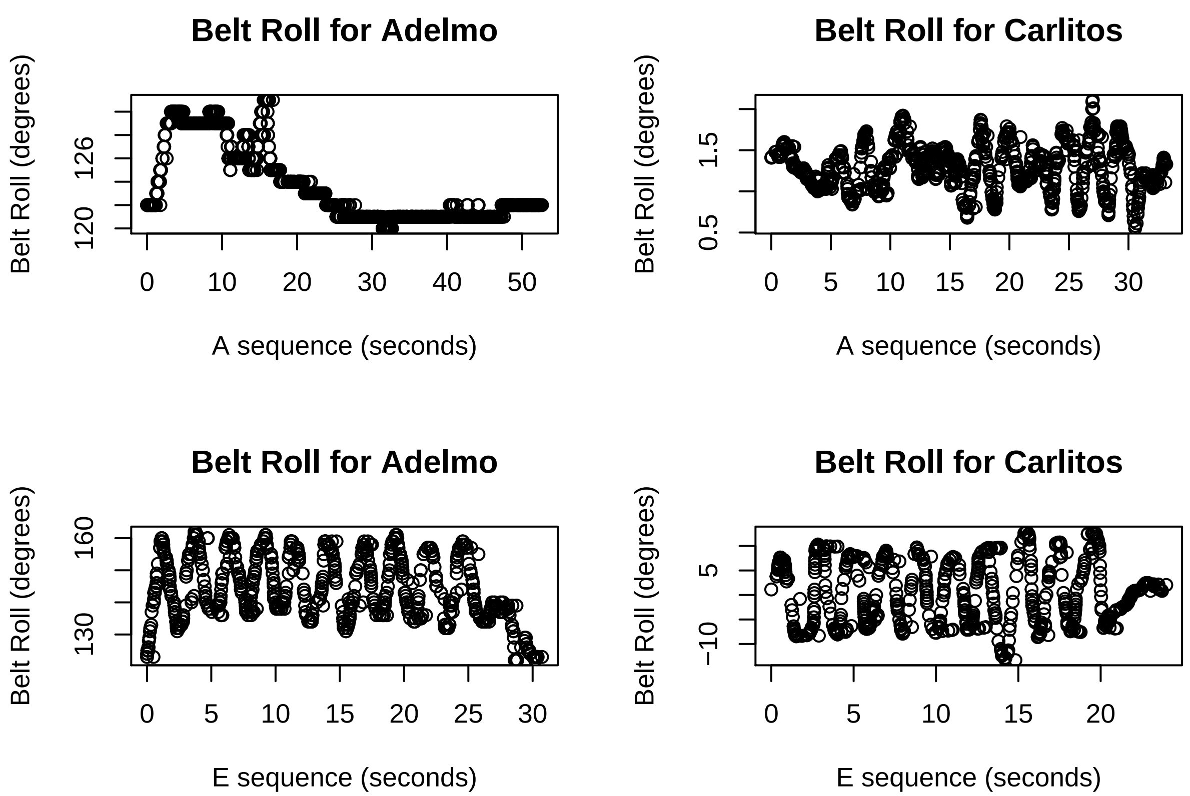
Appendix: Time Series Exploratory Data Analysis

We zero the time distributions by user_name and by classe. Because each of the thirty time series were collected at different times, each one has to be time-zeroed individually. As an example, we compare the A sequence for two user_names for the roll of the belt measurement.

```
trg_data <- mutate(training_all_data, rel_time = as.numeric(paste(raw_timestamp_part_1,
                                raw_timestamp_part_2,sep=".")))

trg_adelmo_A <- filter(trg_data,user_name == "adelmo" & classe == "A")
trg_adelmo_B <- filter(trg_data,user_name == "adelmo" & classe == "B")
trg_adelmo_C <- filter(trg_data,user_name == "adelmo" & classe == "C")
trg_adelmo_D <- filter(trg_data,user_name == "adelmo" & classe == "D")
```

```
trg_adelmo_E <- filter(trg_data,user_name == "adelmo" & classe == "E")

trg_data_adelmo_A_left <- mutate(trg_adelmo_A, time_left = rel_time - min(rel_time))
trg_data_adelmo_B_left <- mutate(trg_adelmo_B, time_left = rel_time - min(rel_time))
trg_data_adelmo_C_left <- mutate(trg_adelmo_C, time_left = rel_time - min(rel_time))
trg_data_adelmo_D_left <- mutate(trg_adelmo_D, time_left = rel_time - min(rel_time))
trg_data_adelmo_E_left <- mutate(trg_adelmo_E, time_left = rel_time - min(rel_time))

trg_carlitos_A <- filter(trg_data,user_name == "carlitos" & classe == "A")
trg_carlitos_B <- filter(trg_data,user_name == "carlitos" & classe == "B")
trg_carlitos_C <- filter(trg_data,user_name == "carlitos" & classe == "C")
trg_carlitos_D <- filter(trg_data,user_name == "carlitos" & classe == "D")
trg_carlitos_E <- filter(trg_data,user_name == "carlitos" & classe == "E")

trg_data_carlitos_A_left <- mutate(trg_carlitos_A, time_left = rel_time - min(rel_time))
trg_data_carlitos_B_left <- mutate(trg_carlitos_B, time_left = rel_time - min(rel_time))
trg_data_carlitos_C_left <- mutate(trg_carlitos_C, time_left = rel_time - min(rel_time))
trg_data_carlitos_D_left <- mutate(trg_carlitos_D, time_left = rel_time - min(rel_time))
trg_data_carlitos_E_left <- mutate(trg_carlitos_E, time_left = rel_time - min(rel_time))

trg_charles_A <- filter(trg_data,user_name == "charles" & classe == "A")
trg_charles_B <- filter(trg_data,user_name == "charles" & classe == "B")
trg_charles_C <- filter(trg_data,user_name == "charles" & classe == "C")
trg_charles_D <- filter(trg_data,user_name == "charles" & classe == "D")
trg_charles_E <- filter(trg_data,user_name == "charles" & classe == "E")

trg_data_charles_A_left <- mutate(trg_charles_A, time_left = rel_time - min(rel_time))
trg_data_charles_B_left <- mutate(trg_charles_B, time_left = rel_time - min(rel_time))
trg_data_charles_C_left <- mutate(trg_charles_C, time_left = rel_time - min(rel_time))
trg_data_charles_D_left <- mutate(trg_charles_D, time_left = rel_time - min(rel_time))
trg_data_charles_E_left <- mutate(trg_charles_E, time_left = rel_time - min(rel_time))

trg_eurico_A <- filter(trg_data,user_name == "eurico" & classe == "A")
trg_eurico_B <- filter(trg_data,user_name == "eurico" & classe == "B")
trg_eurico_C <- filter(trg_data,user_name == "eurico" & classe == "C")
trg_eurico_D <- filter(trg_data,user_name == "eurico" & classe == "D")
trg_eurico_E <- filter(trg_data,user_name == "eurico" & classe == "E")

trg_data_eurico_A_left <- mutate(trg_eurico_A, time_left = rel_time - min(rel_time))
trg_data_eurico_B_left <- mutate(trg_eurico_B, time_left = rel_time - min(rel_time))
trg_data_eurico_C_left <- mutate(trg_eurico_C, time_left = rel_time - min(rel_time))
trg_data_eurico_D_left <- mutate(trg_eurico_D, time_left = rel_time - min(rel_time))
trg_data_eurico_E_left <- mutate(trg_eurico_E, time_left = rel_time - min(rel_time))

trg_jeremy_A <- filter(trg_data,user_name == "jeremy" & classe == "A")
trg_jeremy_B <- filter(trg_data,user_name == "jeremy" & classe == "B")
trg_jeremy_C <- filter(trg_data,user_name == "jeremy" & classe == "C")
trg_jeremy_D <- filter(trg_data,user_name == "jeremy" & classe == "D")
trg_jeremy_E <- filter(trg_data,user_name == "jeremy" & classe == "E")

trg_data_jeremy_A_left <- mutate(trg_jeremy_A, time_left = rel_time - min(rel_time))
trg_data_jeremy_B_left <- mutate(trg_jeremy_B, time_left = rel_time - min(rel_time))
trg_data_jeremy_C_left <- mutate(trg_jeremy_C, time_left = rel_time - min(rel_time))
```

```r
trg_data_jeremy_D_left <- mutate(trg_jeremy_D, time_left = rel_time - min(rel_time))
trg_data_jeremy_E_left <- mutate(trg_jeremy_E, time_left = rel_time - min(rel_time))

trg_pedro_A <- filter(trg_data,user_name == "pedro" & classe == "A")
trg_pedro_B <- filter(trg_data,user_name == "pedro" & classe == "B")
trg_pedro_C <- filter(trg_data,user_name == "pedro" & classe == "C")
trg_pedro_D <- filter(trg_data,user_name == "pedro" & classe == "D")
trg_pedro_E <- filter(trg_data,user_name == "pedro" & classe == "E")

trg_data_pedro_A_left <- mutate(trg_pedro_A, time_left = rel_time - min(rel_time))
trg_data_pedro_B_left <- mutate(trg_pedro_B, time_left = rel_time - min(rel_time))
trg_data_pedro_C_left <- mutate(trg_pedro_C, time_left = rel_time - min(rel_time))
trg_data_pedro_D_left <- mutate(trg_pedro_D, time_left = rel_time - min(rel_time))
trg_data_pedro_E_left <- mutate(trg_pedro_E, time_left = rel_time - min(rel_time))

par(mfrow=c(2,2))
plot(trg_data_adelmo_A_left$time_left,trg_data_adelmo_A_left$roll_belt,
     main="Belt Roll for Adelmo", xlab="A sequence (seconds)", ylab="Belt Roll (degrees)")
plot(trg_data_carlitos_A_left$time_left,trg_data_carlitos_A_left$roll_belt,
     main="Belt Roll for Carlitos", xlab="A sequence (seconds)", ylab="Belt Roll (degrees)")
plot(trg_data_adelmo_E_left$time_left,trg_data_adelmo_E_left$roll_belt,
     main="Belt Roll for Adelmo", xlab="E sequence (seconds)", ylab="Belt Roll (degrees)")
plot(trg_data_carlitos_E_left$time_left,trg_data_carlitos_E_left$roll_belt,
     main="Belt Roll for Carlitos", xlab="E sequence (seconds)", ylab="Belt Roll (degrees)")
```



Appendix: Aggregated Time Bin Exploratory Data Analysis

The aggregated time bin data contains calculated measures from the time bin data in time windows that vary between 0.5 seconds and 2.5 seconds. The Euler angles for sensors located at the belt, arm (glove), forearm, and dumbbell as magnitude quantities for the x,y,z measurements in the time series data are:

- Kurtosis and Skewness.
- Minimum, Maximum, and Average.
- Amplitude.
- Variance and Standard Deviation.

Here are the time window measurements after removal of several columns that only contained zeros or NAs:

- kurtosis_yaw_belt
- skewness_yaw_belt
- kurtosis_yaw_dumbbell
- skewness_yaw_dumbbell
- kurtosis_yaw_forearm
- skewness_yaw_forearm
- amplitude_yaw_dumbbell
- amplitude_yaw_forearm
- amplitude_yaw_belt

```r
training_nonblanks_clean_time <- filter(training_all_clean, kurtosis_roll_belt != "")
training_sdvar_sel_clean_all <- select(training_nonblanks_clean_time,c("user_name",
        "classe","raw_timestamp_part_1","raw_timestamp_part_2","cvtd_timestamp",
        "new_window","num_window","kurtosis_roll_belt","kurtosis_picth_belt",
        "skewness_roll_belt",
        "skewness_roll_belt.1","max_roll_belt","max_picth_belt",
        "max_yaw_belt","min_roll_belt","min_pitch_belt","min_yaw_belt","amplitude_roll_belt",
        "amplitude_pitch_belt","var_total_accel_belt","avg_roll_belt",
        "stddev_roll_belt","var_roll_belt","avg_pitch_belt","stddev_pitch_belt","var_pitch_belt",
        "avg_yaw_belt","stddev_yaw_belt","var_yaw_belt","var_accel_arm","avg_roll_arm",
        "stddev_roll_arm","var_roll_arm","avg_pitch_arm","stddev_pitch_arm","var_pitch_arm",
        "avg_yaw_arm","stddev_yaw_arm","var_yaw_arm","kurtosis_roll_arm","kurtosis_picth_arm",
        "kurtosis_yaw_arm","skewness_roll_arm","skewness_pitch_arm","skewness_yaw_arm",
        "max_roll_arm","max_picth_arm","max_yaw_arm","min_roll_arm","min_pitch_arm",
        "min_yaw_arm","amplitude_roll_arm","amplitude_pitch_arm","amplitude_yaw_arm",
        "kurtosis_roll_dumbbell","kurtosis_picth_dumbbell",
        "skewness_roll_dumbbell","skewness_pitch_dumbbell",
        "max_roll_dumbbell","max_picth_dumbbell","max_yaw_dumbbell","min_roll_dumbbell",
        "min_pitch_dumbbell","min_yaw_dumbbell","amplitude_roll_dumbbell","amplitude_pitch_dumbbell",
        "total_accel_dumbbell","var_accel_dumbbell","avg_roll_dumbbell",
        "stddev_roll_dumbbell","var_roll_dumbbell","avg_pitch_dumbbell","stddev_pitch_dumbbell",
        "var_pitch_dumbbell","avg_yaw_dumbbell","stddev_yaw_dumbbell","var_yaw_dumbbell",
        "kurtosis_roll_forearm","kurtosis_picth_forearm",
        "skewness_roll_forearm","skewness_pitch_forearm",
        "max_roll_forearm","max_picth_forearm","max_yaw_forearm","min_roll_forearm",
        "min_pitch_forearm","min_yaw_forearm","amplitude_roll_forearm","amplitude_pitch_forearm",
        "total_accel_forearm","var_accel_forearm","avg_roll_forearm",
        "stddev_roll_forearm","var_roll_forearm","avg_pitch_forearm","stddev_pitch_forearm",
        "var_pitch_forearm","avg_yaw_forearm","stddev_yaw_forearm","var_yaw_forearm"))
```

Here are the counts by user_name and classe for the time bin data.

```r
kable(table(training_sdvar_sel_clean_all$user_name, training_sdvar_sel_clean_all$classe))
```

	A	B	C	D	E
adelmo	21	14	13	5	22
carlitos	12	16	8	8	12
charles	21	16	16	14	14
eurico	18	9	7	12	8
jeremy	18	14	16	16	12
pedro	14	9	9	11	11

The relevance of using machine learning for data with many variables is evident when we plot selected variables for the time bin series. There are too many combinations of scatter plots for us to plot and we do not need to. What we need to do is use the functions at our disposal to find the level of correlation between the variables in our data, and subtract those with too high a correlation. We are getting ahead of ourselves with the plots showing below because we will later determine the level of correlation for the variables in our training data, yet it's worth using that advance knowlegde here to stress the point that the need for a machine learning analysis becomes evident when there is a very large number of correlations that can be calculated from the variables in our data.

Appendix: Time Bin Feature Selection

We generate the correlation matrix for our data, and use it to generate the list of features in our data with pair-wise correlation of 0.75 or greater.

```
set.seed(22)
training_sdvar_cor <- training_sdvar_sel_clean_all[,8:100]
correlationMatrixSDVAR <- cor(training_sdvar_sel_clean_all[,8:100], use="complete.obs")
highlyCorrelatedSDVAR75 <- findCorrelation(correlationMatrixSDVAR, cutoff=0.75)
names(training_sdvar_cor[,highlyCorrelatedSDVAR75])
```

```
##  [1] "min_pitch_belt"            "avg_roll_belt"
##  [3] "max_picth_belt"            "max_roll_belt"
##  [5] "avg_yaw_belt"              "min_pitch_dumbbell"
##  [7] "amplitude_pitch_dumbbell" "stddev_roll_dumbbell"
##  [9] "amplitude_roll_dumbbell"  "max_picth_arm"
## [11] "stddev_yaw_dumbbell"      "stddev_pitch_dumbbell"
## [13] "amplitude_pitch_arm"      "avg_pitch_forearm"
## [15] "stddev_roll_forearm"      "avg_yaw_dumbbell"
## [17] "stddev_yaw_arm"           "amplitude_pitch_belt"
## [19] "stddev_roll_belt"         "amplitude_yaw_arm"
## [21] "stddev_pitch_arm"         "kurtosis_roll_forearm"
## [23] "amplitude_roll_arm"       "max_yaw_forearm"
## [25] "min_yaw_forearm"          "amplitude_pitch_forearm"
## [27] "stddev_pitch_belt"        "min_pitch_arm"
## [29] "max_yaw_dumbbell"         "min_yaw_dumbbell"
## [31] "amplitude_roll_belt"      "amplitude_roll_forearm"
## [33] "stddev_yaw_belt"          "stddev_yaw_forearm"
## [35] "stddev_pitch_forearm"     "var_roll_belt"
## [37] "kurtosis_picth_dumbbell"  "min_roll_arm"
## [39] "max_roll_arm"             "var_roll_arm"
## [41] "min_yaw_belt"             "kurtosis_roll_belt"
```

We use this list to remove these highly correlated features from the data we will use in our models.

```
training_sdvar_sel_clean <- select(training_sdvar_sel_clean_all,c("user_name",
        "classe","raw_timestamp_part_1","raw_timestamp_part_2","cvtd_timestamp",
```

```
        "new_window","num_window","kurtosis_roll_belt","skewness_roll_belt",
        "skewness_roll_belt.1","min_roll_belt",
        "var_roll_belt","avg_pitch_belt","var_pitch_belt",
        "var_yaw_belt","var_accel_arm","avg_roll_arm",
        "stddev_roll_arm","avg_pitch_arm","var_pitch_arm",
        "avg_yaw_arm","var_yaw_arm","kurtosis_roll_arm","kurtosis_picth_arm",
        "kurtosis_yaw_arm","skewness_roll_arm","skewness_pitch_arm","skewness_yaw_arm",
        "max_yaw_arm","min_yaw_arm","kurtosis_picth_dumbbell",
        "skewness_roll_dumbbell","skewness_pitch_dumbbell",
        "max_roll_dumbbell","max_picth_dumbbell","min_roll_dumbbell",
        "min_yaw_dumbbell","total_accel_dumbbell","var_accel_dumbbell","avg_roll_dumbbell",
        "var_roll_dumbbell","avg_pitch_dumbbell","stddev_pitch_dumbbell",
        "var_pitch_dumbbell","var_yaw_dumbbell","kurtosis_picth_forearm",
        "skewness_roll_forearm","skewness_pitch_forearm",
        "max_picth_forearm","min_roll_forearm","min_pitch_forearm",
        "total_accel_forearm","var_accel_forearm","avg_roll_forearm","var_roll_forearm",
        "var_pitch_forearm","avg_yaw_forearm","var_yaw_forearm"))
```

We then generate the model accuracy contribution of each feature in our data using the Recursive Feature Elimination (RFE) algorithm. This algorithm evaluates the contribution of each feature in steps, beginning with all features. Beginning with the feature that accounts for the least variability in the data, the RFE algorithm removes each feature at a time, and calculates the accuracy of the model with the sequentially reducting list of features.

```
set.seed(22)
training_sdvar_cor_classe_noNA <- na.omit(training_sdvar_sel_clean)
controlSDVAR2 <- rfeControl(functions=rfFuncs, method="cv", number=10)
resultsSDVAR2 <- rfe(training_sdvar_cor_classe_noNA[,8:58],
                     training_sdvar_cor_classe_noNA$classe, sizes=c(1:30), rfeControl=controlSDVAR2)
print(resultsSDVAR2)
```

```
##
## Recursive feature selection
##
## Outer resampling method: Cross-Validated (10 fold)
##
## Resampling performance over subset size:
##
##  Variables Accuracy  Kappa AccuracySD KappaSD Selected
##          1   0.4638 0.3137    0.13388 0.16593
##          2   0.5273 0.4043    0.13165 0.16254
##          3   0.5870 0.4798    0.09137 0.11497
##          4   0.7335 0.6634    0.11654 0.14695
##          5   0.7757 0.7172    0.11255 0.14228
##          6   0.7562 0.6923    0.08007 0.10144
##          7   0.7958 0.7411    0.10984 0.13931
##          8   0.8138 0.7640    0.08791 0.11205
##          9   0.8049 0.7529    0.09468 0.12050
##         10   0.7915 0.7359    0.09777 0.12441
##         11   0.8006 0.7475    0.10266 0.13060
##         12   0.7906 0.7350    0.07150 0.09022
##         13   0.7954 0.7412    0.08279 0.10429
##         14   0.8041 0.7518    0.07217 0.09165
##         15   0.8170 0.7685    0.06273 0.07966
```

```
##          16   0.8095 0.7593    0.07193 0.08981
##          17   0.8188 0.7709    0.07545 0.09423
##          18   0.8225 0.7749    0.06800 0.08670
##          19   0.8219 0.7745    0.07437 0.09502
##          20   0.8225 0.7755    0.05811 0.07271
##          21   0.8086 0.7576    0.06663 0.08423
##          22   0.8179 0.7687    0.07194 0.09202
##          23   0.8269 0.7807    0.05900 0.07419
##          24   0.8267 0.7797    0.06728 0.08676
##          25   0.8213 0.7730    0.06529 0.08381
##          26   0.8267 0.7802    0.07353 0.09378
##          27   0.8302 0.7847    0.06522 0.08384
##          28   0.8311 0.7860    0.06779 0.08556        *
##          29   0.8234 0.7762    0.08594 0.10812
##          30   0.8265 0.7798    0.06845 0.08751
##          51   0.8032 0.7496    0.06628 0.08480
##
## The top 5 variables (out of 28):
##    var_roll_belt, min_roll_belt, var_accel_dumbbell, avg_roll_dumbbell, avg_pitch_belt
```

For our time bin data, these are the best predictors. The accuracy plot shows the accuracy of a model of the data as each least-contributing feature is removed from the model. This procedure is equivalent to a stepwise classification (the case here) or regression analysis of a dataset that goes backwards from the largest number of predictors (features).

```r
predictors(resultsSDVAR2)
```

```
##  [1] "var_roll_belt"         "min_roll_belt"
##  [3] "var_accel_dumbbell"    "avg_roll_dumbbell"
##  [5] "avg_pitch_belt"        "min_roll_forearm"
##  [7] "var_pitch_belt"        "var_yaw_belt"
##  [9] "avg_pitch_dumbbell"    "max_picth_dumbbell"
## [11] "max_roll_dumbbell"     "avg_roll_forearm"
## [13] "total_accel_dumbbell"  "avg_roll_arm"
## [15] "var_pitch_forearm"     "min_roll_dumbbell"
## [17] "max_picth_forearm"     "stddev_pitch_dumbbell"
## [19] "var_pitch_dumbbell"    "min_pitch_forearm"
## [21] "var_yaw_arm"           "var_yaw_dumbbell"
## [23] "var_accel_forearm"     "min_yaw_arm"
## [25] "var_accel_arm"         "var_roll_dumbbell"
## [27] "var_roll_forearm"      "var_yaw_forearm"
```

Appendix: Caret Models Applied to the Aggregated Training Data

To mimic a test dataset, we resample the training data. We use this mock testing data in-place before we run on the actual testing data for this analysis. We make sure that each sequence (A to E) is resampled at the same frequency (20 each).

```r
table(training_sdvar_cor_classe_noNA$classe)
```

```
##
##  A  B  C  D  E
## 54 48 37 35 43
```

```r
set.seed(22)
training_sdvar_cor_classe_noNA_A <- filter(training_sdvar_cor_classe_noNA, classe == "A")
```

```
training_sdvar_cor_classe_noNA_B <- filter(training_sdvar_cor_classe_noNA, classe == "B")
training_sdvar_cor_classe_noNA_C <- filter(training_sdvar_cor_classe_noNA, classe == "C")
training_sdvar_cor_classe_noNA_D <- filter(training_sdvar_cor_classe_noNA, classe == "D")
training_sdvar_cor_classe_noNA_E <- filter(training_sdvar_cor_classe_noNA, classe == "E")

testing_sdvar_cor_classe_noNA_A <- sample_n(training_sdvar_cor_classe_noNA_A, 20, replace=FALSE)
testing_sdvar_cor_classe_noNA_B <- sample_n(training_sdvar_cor_classe_noNA_B, 20, replace=FALSE)
testing_sdvar_cor_classe_noNA_C <- sample_n(training_sdvar_cor_classe_noNA_C, 20, replace=FALSE)
testing_sdvar_cor_classe_noNA_D <- sample_n(training_sdvar_cor_classe_noNA_D, 20, replace=FALSE)
testing_sdvar_cor_classe_noNA_E <- sample_n(training_sdvar_cor_classe_noNA_E, 20, replace=FALSE)

testing_sdvar_cor_classe_noNA <- rbind(testing_sdvar_cor_classe_noNA_A,
                                       testing_sdvar_cor_classe_noNA_B,
                                       testing_sdvar_cor_classe_noNA_C,
                                       testing_sdvar_cor_classe_noNA_D,
                                       testing_sdvar_cor_classe_noNA_E)
```

We setup repeated cross validation resampling to use in our models.

```
set.seed(22)
training_sdvar_cor_classe_noNA <- training_sdvar_cor_classe_noNA[,c(2,8:58)]
controlSDVAR <- trainControl(method="repeatedcv", number=10)
```

Here are the results for the Least Squares Support Vector Machines with Polynomial Kernel (method="svmPoly" in caret train function) model.

```
set.seed(22)
modelSDVARsvmPoly <- train(factor(classe) ~ ., data=training_sdvar_cor_classe_noNA,
                       method="svmPoly", preProcess=c("scale","center"), trControl=controlSDVAR)
print(modelSDVARsvmPoly)
```

```
## Support Vector Machines with Polynomial Kernel
##
## 217 samples
##  51 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (51), centered (51)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 196, 198, 194, 194, 196, 197, ...
## Resampling results across tuning parameters:
##
##   degree  scale  C     Accuracy   Kappa
##   1       0.001  0.25  0.2487372   0.000000000
##   1       0.001  0.50  0.2487372   0.000000000
##   1       0.001  1.00  0.2443894  -0.005612245
##   1       0.010  0.25  0.2959217   0.071536786
##   1       0.010  0.50  0.4214352   0.259121274
##   1       0.010  1.00  0.5788809   0.466285479
##   1       0.100  0.25  0.6046426   0.498812543
##   1       0.100  0.50  0.6328683   0.535950793
##   1       0.100  1.00  0.6125989   0.510025175
##   2       0.001  0.25  0.2487372   0.000000000
##   2       0.001  0.50  0.2443894  -0.005612245
##   2       0.001  1.00  0.2496525   0.004528391
```

```
##   2       0.010  0.25  0.4757479   0.328647187
##   2       0.010  0.50  0.6114140   0.507088483
##   2       0.010  1.00  0.6285483   0.529103725
##   2       0.100  0.25  0.6278216   0.530560268
##   2       0.100  0.50  0.6109036   0.510163533
##   2       0.100  1.00  0.6056405   0.503167067
##   3       0.001  0.25  0.2487372   0.000000000
##   3       0.001  0.50  0.2494549   0.002936451
##   3       0.001  1.00  0.3373014   0.132057159
##   3       0.010  0.25  0.6015649   0.493677212
##   3       0.010  0.50  0.6422224   0.546410282
##   3       0.010  1.00  0.6684198   0.580856296
##   3       0.100  0.25  0.6215964   0.522589211
##   3       0.100  0.50  0.6215964   0.522589211
##   3       0.100  1.00  0.6215964   0.522589211
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were degree = 3, scale = 0.01 and C
##  = 1.
```

```
importanceSDVARsvmPoly <- varImp(modelSDVARsvmPoly, scale=TRUE)
print(importanceSDVARsvmPoly)
```

```
## ROC curve variable importance
##
##   variables are sorted by maximum importance across the classes
##   only 20 most important variables shown (out of 51)
##
##                            A     B       C      D      E
## var_pitch_belt          39.456 39.46 100.000 42.996 14.297
## var_roll_belt           30.944 27.28  91.191 36.950 30.944
## var_accel_dumbbell      66.631 66.63  76.382 88.272 38.685
## avg_roll_dumbbell       77.715 39.12  18.840 85.393 77.715
## min_roll_forearm         7.151 81.26  18.849  7.151 81.259
## max_roll_dumbbell       61.527 14.11  14.105 77.907 61.527
## stddev_pitch_dumbbell   51.354 10.92   9.963 70.565 51.354
## var_pitch_dumbbell      51.354 10.92   9.963 70.565 51.354
## var_yaw_belt            19.383 42.03  66.582 19.383 42.029
## max_picth_dumbbell      65.430 41.83  31.457 42.852 65.430
## avg_pitch_dumbbell      49.307 39.93  24.463 64.806 49.307
## var_roll_forearm         4.537 56.03  17.253  5.782 56.030
## var_roll_dumbbell       53.018 24.85  13.839 44.796 53.018
## var_yaw_dumbbell        46.107  1.31   3.269 52.714 46.107
## var_accel_forearm       38.685 35.31  49.405 35.313 38.685
## var_yaw_forearm         25.153 48.73  37.953 25.153 48.725
## total_accel_dumbbell    47.890 47.89  47.890 47.890 22.946
## skewness_pitch_dumbbell 47.347 47.35  47.347 47.347 31.775
## min_yaw_dumbbell        43.599 43.60  43.599 43.599  2.407
## kurtosis_picth_forearm   3.239 43.18   9.875  7.942 43.179
```

```
confusionMatrix(testing_sdvar_cor_classe_noNA$classe,
                predict(modelSDVARsvmPoly,testing_sdvar_cor_classe_noNA))
```

```
## Confusion Matrix and Statistics
##
```

```
##           Reference
## Prediction  A  B  C  D  E
##          A 19  0  1  0  0
##          B  1 18  1  0  0
##          C  0  1 19  0  0
##          D  0  1  1 18  0
##          E  0  0  0  0 20
##
## Overall Statistics
##
##                Accuracy : 0.94
##                  95% CI : (0.874, 0.9777)
##     No Information Rate : 0.22
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.925
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9500   0.9000   0.8636   1.0000      1.0
## Specificity            0.9875   0.9750   0.9872   0.9756      1.0
## Pos Pred Value         0.9500   0.9000   0.9500   0.9000      1.0
## Neg Pred Value         0.9875   0.9750   0.9625   1.0000      1.0
## Prevalence             0.2000   0.2000   0.2200   0.1800      0.2
## Detection Rate         0.1900   0.1800   0.1900   0.1800      0.2
## Detection Prevalence   0.2000   0.2000   0.2000   0.2000      0.2
## Balanced Accuracy      0.9688   0.9375   0.9254   0.9878      1.0
```

Here are the results for the Decision Trees (method="C5.0" in caret train function) model.

```r
set.seed(22)
modelSDVARC50 <- train(factor(classe) ~ ., data=training_sdvar_cor_classe_noNA,
                        method="C5.0",
                       preProcess=c("scale","center"), trControl=controlSDVAR)
print(modelSDVARC50)
```

```
## C5.0
##
## 217 samples
##  51 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (51), centered (51)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 196, 198, 194, 194, 196, 197, ...
## Resampling results across tuning parameters:
##
##   model  winnow  trials  Accuracy   Kappa
##   rules  FALSE    1      0.6533185  0.5633420
##   rules  FALSE   10      0.7243997  0.6521083
##   rules  FALSE   20      0.7571458  0.6935163
##   rules   TRUE    1      0.6791563  0.5965507
```

```
##   rules   TRUE   10      0.7489360  0.6838114
##   rules   TRUE   20      0.7624340  0.7010709
##   tree   FALSE    1      0.6348547  0.5396057
##   tree   FALSE   10      0.7419275  0.6746432
##   tree   FALSE   20      0.7470803  0.6804966
##   tree    TRUE    1      0.6821747  0.6010889
##   tree    TRUE   10      0.7659070  0.7050102
##   tree    TRUE   20      0.7753903  0.7173686
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were trials = 20, model = tree
##  and winnow = TRUE.
```

```r
importanceSDVARC50 <- varImp(modelSDVARC50, scale=TRUE)
print(importanceSDVARC50)
```

```
## C5.0 variable importance
##
##   only 20 most important variables shown (out of 51)
##
##                          Overall
## avg_roll_dumbbell         100.00
## min_roll_belt             100.00
## avg_pitch_belt            100.00
## var_roll_belt             100.00
## var_accel_dumbbell         97.24
## min_roll_forearm           96.31
## max_picth_dumbbell         95.85
## avg_roll_forearm           94.47
## var_pitch_belt             92.63
## min_yaw_arm                86.18
## var_yaw_belt               74.65
## avg_yaw_arm                74.19
## avg_yaw_forearm            52.07
## max_roll_dumbbell           0.00
## avg_pitch_dumbbell          0.00
## skewness_pitch_dumbbell     0.00
## var_yaw_arm                 0.00
## var_pitch_arm               0.00
## var_yaw_forearm             0.00
## kurtosis_roll_arm           0.00
```

```r
confusionMatrix(testing_sdvar_cor_classe_noNA$classe,
                predict(modelSDVARC50,testing_sdvar_cor_classe_noNA))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  A  B  C  D  E
##          A 20  0  0  0  0
##          B  0 20  0  0  0
##          C  0  0 20  0  0
##          D  0  0  0 20  0
##          E  0  0  0  0 20
##
```

```
## Overall Statistics
##
##                Accuracy : 1
##                  95% CI : (0.9638, 1)
##     No Information Rate : 0.2
##     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               1.0      1.0      1.0      1.0      1.0
## Specificity               1.0      1.0      1.0      1.0      1.0
## Pos Pred Value            1.0      1.0      1.0      1.0      1.0
## Neg Pred Value            1.0      1.0      1.0      1.0      1.0
## Prevalence                0.2      0.2      0.2      0.2      0.2
## Detection Rate            0.2      0.2      0.2      0.2      0.2
## Detection Prevalence      0.2      0.2      0.2      0.2      0.2
## Balanced Accuracy         1.0      1.0      1.0      1.0      1.0
```

Here are the results for the Random Forest (method="rf" in caret train function) model.

```
set.seed(22)
modelSDVARrf <- train(factor(classe) ~ ., data=training_sdvar_cor_classe_noNA,
                      method="rf", preProcess=c("scale","center"), trControl=controlSDVAR)
print(modelSDVARrf)
```

```
## Random Forest
##
## 217 samples
##  51 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (51), centered (51)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 196, 198, 194, 194, 196, 197, ...
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa
##    2    0.7593656  0.6940633
##   26    0.7750679  0.7161632
##   51    0.7611962  0.6982367
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 26.
```

```
importanceSDVARrf <- varImp(modelSDVARrf, scale=TRUE)
print(importanceSDVARrf)
```

```
## rf variable importance
##
##   only 20 most important variables shown (out of 51)
##
```

```
##                       Overall
## var_roll_belt      100.000
## avg_roll_dumbbell   78.596
## min_roll_forearm    69.591
## var_accel_dumbbell  61.990
## avg_pitch_belt      46.727
## min_roll_belt       46.041
## avg_roll_forearm    36.112
## max_picth_dumbbell  20.047
## var_pitch_belt      18.639
## avg_pitch_dumbbell  14.347
## var_yaw_belt        12.704
## max_picth_forearm   12.307
## var_pitch_forearm   11.902
## max_roll_dumbbell   11.870
## var_yaw_arm         11.619
## var_accel_arm        8.787
## min_roll_dumbbell    8.693
## avg_roll_arm         8.143
## min_pitch_forearm    7.854
## var_roll_forearm     7.575
```

```r
confusionMatrix(testing_sdvar_cor_classe_noNA$classe,
                predict(modelSDVARrf,testing_sdvar_cor_classe_noNA))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  A  B  C  D  E
##          A 20  0  0  0  0
##          B  0 20  0  0  0
##          C  0  0 20  0  0
##          D  0  0  0 20  0
##          E  0  0  0  0 20
##
## Overall Statistics
##
##                Accuracy : 1
##                  95% CI : (0.9638, 1)
##     No Information Rate : 0.2
##     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               1.0      1.0      1.0      1.0      1.0
## Specificity               1.0      1.0      1.0      1.0      1.0
## Pos Pred Value            1.0      1.0      1.0      1.0      1.0
## Neg Pred Value            1.0      1.0      1.0      1.0      1.0
## Prevalence                0.2      0.2      0.2      0.2      0.2
## Detection Rate            0.2      0.2      0.2      0.2      0.2
```

```
## Detection Prevalence      0.2      0.2      0.2      0.2      0.2
## Balanced Accuracy         1.0      1.0      1.0      1.0      1.0
```

Here are the results for the Bagged Trees (method="treebag" in caret train function) model.

```r
set.seed(22)
modelSDVARtreebag <- train(factor(classe) ~ ., data=training_sdvar_cor_classe_noNA,
                           method="treebag", preProcess=c("scale","center"),            trControl=contr
print(modelSDVARtreebag)
```

```
## Bagged CART
##
## 217 samples
##  51 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (51), centered (51)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 196, 198, 194, 194, 196, 197, ...
## Resampling results:
##
##   Accuracy   Kappa
##   0.7392783  0.670805
```

```r
importanceSDVARtreebag <- varImp(modelSDVARtreebag, scale=TRUE)
print(importanceSDVARtreebag)
```

```
## treebag variable importance
##
##   only 20 most important variables shown (out of 51)
##
##                       Overall
## avg_roll_dumbbell      100.00
## var_accel_dumbbell      82.05
## var_roll_belt           72.50
## min_roll_belt           71.26
## min_roll_forearm        69.85
## avg_pitch_belt          47.06
## avg_roll_forearm        46.14
## var_pitch_belt          41.96
## max_picth_dumbbell      32.75
## var_yaw_belt            26.38
## var_pitch_forearm       25.13
## var_accel_arm           24.15
## skewness_roll_belt      23.02
## avg_pitch_dumbbell      22.62
## var_yaw_arm             21.83
## skewness_roll_belt.1    20.70
## min_roll_dumbbell       19.99
## max_roll_dumbbell       19.38
## min_pitch_forearm       19.38
## avg_roll_arm            19.03
```

```r
confusionMatrix(testing_sdvar_cor_classe_noNA$classe,
                predict(modelSDVARtreebag,testing_sdvar_cor_classe_noNA))
```

```
## Confusion Matrix and Statistics
```

```
##
##           Reference
## Prediction  A  B  C  D  E
##          A 19  1  0  0  0
##          B  0 20  0  0  0
##          C  0  0 20  0  0
##          D  0  0  0 20  0
##          E  0  0  0  0 20
##
## Overall Statistics
##
##                Accuracy : 0.99
##                  95% CI : (0.9455, 0.9997)
##     No Information Rate : 0.21
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9875
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   0.9524      1.0      1.0      1.0
## Specificity            0.9877   1.0000      1.0      1.0      1.0
## Pos Pred Value         0.9500   1.0000      1.0      1.0      1.0
## Neg Pred Value         1.0000   0.9875      1.0      1.0      1.0
## Prevalence             0.1900   0.2100      0.2      0.2      0.2
## Detection Rate         0.1900   0.2000      0.2      0.2      0.2
## Detection Prevalence   0.2000   0.2000      0.2      0.2      0.2
## Balanced Accuracy      0.9938   0.9762      1.0      1.0      1.0
```

We resample the accuracy and kappa of the four models for all predictors.

```r
set.seed(22)
allModels <- resamples(list(SVMPoly=modelSDVARsvmPoly,
                           DecisionTree=modelSDVARC50,
                           RandomForest=modelSDVARrf,
                           BaggedTrees=modelSDVARtreebag
                           ))
summary(allModels)
```

```
##
## Call:
## summary.resamples(object = allModels)
##
## Models: SVMPoly, DecisionTree, RandomForest, BaggedTrees
## Number of resamples: 10
##
## Accuracy
##                   Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## SVMPoly      0.5909091 0.6233766 0.6521739 0.6684198 0.7265446 0.7619048
## DecisionTree 0.5454545 0.7035573 0.7445652 0.7753903 0.8884439 0.9523810
## RandomForest 0.6818182 0.7175325 0.7663043 0.7750679 0.8260870 0.9047619
## BaggedTrees  0.5454545 0.6818182 0.7445652 0.7392783 0.7826087 0.9047619
```

```
##               NA's
## SVMPoly          0
## DecisionTree     0
## RandomForest     0
## BaggedTrees      0
##
## Kappa
##                   Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## SVMPoly      0.4838710 0.5217044 0.5597683 0.5808563 0.6552233 0.7008547
## DecisionTree 0.4285714 0.6288110 0.6788718 0.7173686 0.8588305 0.9400000
## RandomForest 0.5968586 0.6426142 0.7045461 0.7161632 0.7824912 0.8803419
## BaggedTrees  0.4225722 0.5958194 0.6756971 0.6708050 0.7282581 0.8796562
##               NA's
## SVMPoly          0
## DecisionTree     0
## RandomForest     0
## BaggedTrees      0
```

Appendix: Time Unaggregated Data Feature Selection

```
training_blanks_cv_A <- filter(training_blanks_cv, classe == "A")
training_blanks_cv_B <- filter(training_blanks_cv, classe == "B")
training_blanks_cv_C <- filter(training_blanks_cv, classe == "C")
training_blanks_cv_D <- filter(training_blanks_cv, classe == "D")
training_blanks_cv_E <- filter(training_blanks_cv, classe == "E")

training_blanks_cv_sample_A <- sample_n(training_blanks_cv_A, 100, replace=FALSE)
training_blanks_cv_sample_B <- sample_n(training_blanks_cv_B, 100, replace=FALSE)
training_blanks_cv_sample_C <- sample_n(training_blanks_cv_C, 100, replace=FALSE)
training_blanks_cv_sample_D <- sample_n(training_blanks_cv_D, 100, replace=FALSE)
training_blanks_cv_sample_E <- sample_n(training_blanks_cv_E, 100, replace=FALSE)

training_blanks_cv_sample <- rbind(training_blanks_cv_sample_A,
                                   training_blanks_cv_sample_B,
                                   training_blanks_cv_sample_C,
                                   training_blanks_cv_sample_D,
                                   training_blanks_cv_sample_E)

table(training_blanks_cv_sample$classe)
```

```
##
##   A   B   C   D   E
## 100 100 100 100 100
```

We set-up a resampling method, and find out which fields have a correlation value of 0.75 or higher. These are the fields we remove between the first and second cycle of the analysis, as described in the main body of this work above.

```
set.seed(22)
controlTSCV <- rfeControl(functions=rfFuncs, method="repeatedcv", number=3)

correlationMatrixTSCV <- cor(training_blanks_cv_sample[,1:52], use="complete.obs")
highlyCorrelatedTSCV75 <- findCorrelation(correlationMatrixTSCV, cutoff=0.75)
names(training_blanks_cv_sample[,highlyCorrelatedTSCV75])
```

```
##  [1] "accel_belt_z"      "roll_belt"         "accel_belt_x"
##  [4] "yaw_belt"          "accel_dumbbell_z"  "pitch_belt"
##  [7] "accel_belt_y"      "magnet_dumbbell_x" "accel_dumbbell_y"
## [10] "accel_arm_x"       "accel_dumbbell_x"  "accel_arm_z"
## [13] "magnet_arm_y"      "accel_forearm_y"   "gyros_forearm_y"
## [16] "gyros_arm_x"
```

Here are the contributions for the sequential predictors and the stepwise classification performed usign the RFE algorithm.

```r
resultsTSCV <- rfe(training_blanks_cv_sample[,1:52],
                 training_blanks_cv_sample$classe, sizes=c(1:30), rfeControl=controlTSCV)
print(resultsTSCV)
```

```
##
## Recursive feature selection
##
## Outer resampling method: Cross-Validated (3 fold, repeated 1 times)
##
## Resampling performance over subset size:
##
##  Variables Accuracy  Kappa AccuracySD KappaSD Selected
##          1   0.4380 0.2974    0.02157 0.02710
##          2   0.5559 0.4450    0.05287 0.06610
##          3   0.6519 0.5651    0.05773 0.07214
##          4   0.6679 0.5850    0.05076 0.06349
##          5   0.6780 0.5975    0.06841 0.08550
##          6   0.7220 0.6526    0.06085 0.07598
##          7   0.7401 0.6752    0.08607 0.10742
##          8   0.7521 0.6901    0.07673 0.09580
##          9   0.7460 0.6826    0.05799 0.07233
##         10   0.7500 0.6875    0.04854 0.06060
##         11   0.7560 0.6950    0.04028 0.05030
##         12   0.7720 0.7151    0.06587 0.08227
##         13   0.7940 0.7426    0.05071 0.06332
##         14   0.8040 0.7551    0.04562 0.05696
##         15   0.8100 0.7626    0.06132 0.07656
##         16   0.8020 0.7526    0.04169 0.05202
##         17   0.8101 0.7626    0.05338 0.06663        *
##         18   0.8060 0.7576    0.04831 0.06031
##         19   0.7981 0.7476    0.04375 0.05461
##         20   0.8001 0.7501    0.04499 0.05616
##         21   0.7880 0.7350    0.03058 0.03817
##         22   0.8041 0.7551    0.04377 0.05464
##         23   0.8041 0.7551    0.03946 0.04924
##         24   0.8081 0.7601    0.04279 0.05344
##         25   0.7900 0.7375    0.02732 0.03411
##         26   0.7840 0.7301    0.04648 0.05804
##         27   0.7980 0.7475    0.04561 0.05695
##         28   0.7920 0.7401    0.03826 0.04777
##         29   0.7760 0.7200    0.03645 0.04552
##         30   0.7820 0.7276    0.04056 0.05064
##         52   0.7740 0.7175    0.05252 0.06562
##
## The top 5 variables (out of 17):
```

```
##    roll_belt, pitch_forearm, magnet_dumbbell_z, magnet_belt_z, magnet_belt_y
```

```r
predictors(resultsTSCV)
```

```
##  [1] "roll_belt"            "pitch_forearm"        "magnet_dumbbell_z"
##  [4] "magnet_belt_z"        "magnet_belt_y"        "roll_dumbbell"
##  [7] "accel_dumbbell_y"     "magnet_dumbbell_y"    "accel_forearm_x"
## [10] "magnet_dumbbell_x"    "accel_dumbbell_z"     "roll_forearm"
## [13] "yaw_belt"             "accel_belt_z"         "pitch_belt"
## [16] "total_accel_dumbbell" "magnet_arm_x"
```

Appendix: Training the model using resampled training data and all predictors.

- Random Forest

```r
modelTScvrf <- train(factor(classe) ~ ., data=training_blanks_cv_sample,
                     method="rf", preProcess=c("scale","center"),
                     trControl=TcontrolTS, na.action=na.pass)
print(modelTScvrf)
```

```
## Random Forest
##
## 500 samples
##  52 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (52), centered (52)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 450, 450, 450, 450, 450, 450, ...
## Resampling results across tuning parameters:
##
##   mtry  Accuracy  Kappa
##    2    0.848     0.8100
##   27    0.826     0.7825
##   52    0.826     0.7825
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 2.
```

```r
importanceTSCVrf <- varImp(modelTScvrf, scale=TRUE)
print(importanceTSCVrf)
```

```
## rf variable importance
##
##   only 20 most important variables shown (out of 52)
##
##                   Overall
## pitch_forearm      100.00
## roll_belt           98.75
## magnet_belt_z       78.25
## yaw_belt            71.99
## magnet_dumbbell_y   70.91
## magnet_dumbbell_z   69.06
## magnet_belt_y       67.96
## accel_belt_z        63.89
## roll_dumbbell       62.58
```

```
## accel_forearm_x     61.91
## magnet_dumbbell_x   61.07
## accel_dumbbell_y    58.04
## pitch_belt          54.57
## magnet_arm_y        50.10
## magnet_arm_x        46.78
## magnet_forearm_x    42.57
## accel_dumbbell_x    40.52
## accel_dumbbell_z    39.64
## gyros_dumbbell_y    39.56
## accel_arm_x         38.50
```

- Decision Trees

```
modelTScvC50 <- train(factor(classe) ~ ., data=training_blanks_cv_sample,
                      method="C5.0", preProcess=c("scale","center"),
                      trControl=TcontrolTS, na.action=na.pass)
print(modelTScvC50)
```

```
## C5.0
##
## 500 samples
##  52 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (52), centered (52)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 450, 450, 450, 450, 450, 450, ...
## Resampling results across tuning parameters:
##
##   model  winnow  trials  Accuracy  Kappa
##   rules  FALSE    1      0.686     0.6075
##   rules  FALSE   10      0.796     0.7450
##   rules  FALSE   20      0.830     0.7875
##   rules   TRUE    1      0.638     0.5475
##   rules   TRUE   10      0.766     0.7075
##   rules   TRUE   20      0.798     0.7475
##   tree   FALSE    1      0.704     0.6300
##   tree   FALSE   10      0.820     0.7750
##   tree   FALSE   20      0.820     0.7750
##   tree    TRUE    1      0.648     0.5600
##   tree    TRUE   10      0.760     0.7000
##   tree    TRUE   20      0.816     0.7700
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were trials = 20, model = rules
##  and winnow = FALSE.
```

```
importanceTSCVC50 <- varImp(modelTScvC50, scale=TRUE)
print(importanceTSCVC50)
```

```
## C5.0 variable importance
##
##   only 20 most important variables shown (out of 52)
##
##                     Overall
```

```
## pitch_belt         100.00
## accel_belt_z       100.00
## roll_belt          100.00
## accel_dumbbell_x   100.00
## gyros_belt_z       100.00
## yaw_arm            100.00
## magnet_belt_z      100.00
## gyros_dumbbell_x    99.76
## pitch_forearm       99.76
## gyros_belt_y        99.53
## yaw_belt            99.29
## gyros_belt_x        99.06
## magnet_dumbbell_z   98.59
## gyros_dumbbell_y    98.35
## roll_dumbbell       96.71
## magnet_arm_z        96.47
## gyros_forearm_z     95.53
## magnet_dumbbell_y   91.29
## accel_forearm_x     88.24
## accel_dumbbell_y    83.53
```

- Bagged Trees

```
modelTScvtreebag <- train(factor(classe) ~ ., data=training_blanks_cv_sample,
                          method="treebag", preProcess=c("scale","center"),
                          trControl=TcontrolTS, na.action=na.pass)
print(modelTScvtreebag)
```

```
## Bagged CART
##
## 500 samples
##  52 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (52), centered (52)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 450, 450, 450, 450, 450, 450, ...
## Resampling results:
##
##   Accuracy  Kappa
##   0.796     0.745
```

```
importanceTSCVtreebag <- varImp(modelTScvtreebag, scale=TRUE)
print(importanceTSCVtreebag)
```

```
## treebag variable importance
##
##   only 20 most important variables shown (out of 52)
##
##                    Overall
## roll_belt           100.00
## pitch_forearm        82.47
## magnet_belt_z        60.40
## magnet_dumbbell_z    51.36
## magnet_belt_y        49.26
## roll_dumbbell        47.59
```

```
## pitch_belt           45.85
## magnet_dumbbell_x    45.21
## accel_dumbbell_y     43.99
## accel_forearm_x      43.61
## yaw_belt             42.95
## accel_belt_z         37.44
## magnet_dumbbell_y    33.64
## gyros_dumbbell_y     30.63
## gyros_belt_x         22.21
## yaw_arm              21.01
## magnet_arm_y         19.39
## magnet_arm_x         19.34
## gyros_belt_z         19.01
## roll_arm             17.93
```

- SVM Polynomial Kernel

```r
modelTScvsvmPoly <- train(factor(classe) ~ ., data=training_blanks_cv_sample,
                          method="svmPoly", preProcess=c("scale","center"),
                          trControl=TcontrolTS, na.action=na.pass)
print(modelTScvsvmPoly)
```

```
## Support Vector Machines with Polynomial Kernel
##
## 500 samples
##  52 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (52), centered (52)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 450, 450, 450, 450, 450, 450, ...
## Resampling results across tuning parameters:
##
##   degree  scale  C     Accuracy  Kappa
##   1       0.001  0.25  0.384     0.2300
##   1       0.001  0.50  0.384     0.2300
##   1       0.001  1.00  0.382     0.2275
##   1       0.010  0.25  0.386     0.2325
##   1       0.010  0.50  0.428     0.2850
##   1       0.010  1.00  0.502     0.3775
##   1       0.100  0.25  0.564     0.4550
##   1       0.100  0.50  0.562     0.4525
##   1       0.100  1.00  0.602     0.5025
##   2       0.001  0.25  0.386     0.2325
##   2       0.001  0.50  0.384     0.2300
##   2       0.001  1.00  0.376     0.2200
##   2       0.010  0.25  0.486     0.3575
##   2       0.010  0.50  0.556     0.4450
##   2       0.010  1.00  0.634     0.5425
##   2       0.100  0.25  0.714     0.6425
##   2       0.100  0.50  0.718     0.6475
##   2       0.100  1.00  0.708     0.6350
##   3       0.001  0.25  0.386     0.2325
##   3       0.001  0.50  0.382     0.2275
##   3       0.001  1.00  0.394     0.2425
```

```
##   3       0.010  0.25  0.584     0.4800
##   3       0.010  0.50  0.652     0.5650
##   3       0.010  1.00  0.684     0.6050
##   3       0.100  0.25  0.696     0.6200
##   3       0.100  0.50  0.698     0.6225
##   3       0.100  1.00  0.698     0.6225
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were degree = 2, scale = 0.1 and C
##  = 0.5.
```

```
importanceTSCVsvmPoly <- varImp(modelTScvsvmPoly, scale=TRUE)
print(importanceTSCVsvmPoly)
```

```
## ROC curve variable importance
##
##   variables are sorted by maximum importance across the classes
##   only 20 most important variables shown (out of 52)
##
##                        A      B     C     D      E
## pitch_forearm      70.19 100.00 70.19 70.19 100.00
## accel_forearm_x    33.32  89.12 41.15 25.94  89.12
## magnet_arm_y       22.99  69.43 78.90 22.99  69.43
## magnet_forearm_x   46.03  71.41 39.99 23.88  71.41
## magnet_dumbbell_z  55.72  16.97 70.39 44.88  55.72
## magnet_arm_x       38.68  67.47 69.11 38.68  67.47
## magnet_dumbbell_x  67.13  67.13 67.13 67.13  57.22
## pitch_dumbbell     52.53  56.99 52.53 63.45  56.99
## accel_arm_x        50.69  62.81 57.27 50.69  62.81
## magnet_belt_y      29.61  29.61 61.23 29.61  22.80
## accel_dumbbell_z   60.77  60.77 60.77 60.77  22.36
## pitch_arm          18.89  38.86 56.87 18.60  38.86
## magnet_arm_z       46.29  46.29 55.43 46.29  28.38
## accel_dumbbell_x   55.26  55.26 55.26 55.26  53.59
## roll_dumbbell      47.91  45.35 25.39 52.95  47.91
## magnet_belt_z      12.57  12.57 46.98 12.57  11.30
## roll_arm           44.24  44.24 44.24 44.24  22.38
## total_accel_arm    27.84  44.21 31.51 27.84  44.21
## yaw_dumbbell       35.64  35.64 35.64 40.33  22.36
## yaw_forearm        31.13  39.93 31.13 31.13  39.93
```

We resample the accuracy and kappa of the four models for all predictors using resampled training data as mock test data.

```
allModelscv <- resamples(list(SVMPoly=modelTScvsvmPoly,
                               DecisionTree=modelTScvC50,
                               RandomForest=modelTScvrf,
                               BaggedTrees=modelTScvtreebag
))
summary(allModelscv)
```

```
##
## Call:
## summary.resamples(object = allModelscv)
##
## Models: SVMPoly, DecisionTree, RandomForest, BaggedTrees
```

```
## Number of resamples: 10
##
## Accuracy
##              Min. 1st Qu. Median  Mean 3rd Qu. Max. NA's
## SVMPoly      0.60   0.660   0.73 0.718   0.760 0.82    0
## DecisionTree 0.74   0.765   0.83 0.830   0.890 0.94    0
## RandomForest 0.78   0.790   0.85 0.848   0.875 0.98    0
## BaggedTrees  0.74   0.780   0.78 0.796   0.820 0.86    0
##
## Kappa
##               Min. 1st Qu. Median   Mean 3rd Qu.  Max. NA's
## SVMPoly      0.500 0.57500 0.6625 0.6475 0.70000 0.775    0
## DecisionTree 0.675 0.70625 0.7875 0.7875 0.86250 0.925    0
## RandomForest 0.725 0.73750 0.8125 0.8100 0.84375 0.975    0
## BaggedTrees  0.675 0.72500 0.7250 0.7450 0.77500 0.825    0
```

Appendix: Training the model using resampled training data and the least correlated predictors.

- Random Forest

```
modelTScv2rf <- train(factor(classe) ~ pitch_belt + yaw_belt + gyros_belt_x +
                  gyros_belt_y + gyros_belt_z +
                  magnet_belt_y + magnet_belt_z + roll_arm + pitch_arm + yaw_arm +
                  accel_belt_y + accel_belt_z + magnet_belt_x +  magnet_arm_y + roll_dumbbell +
                  pitch_dumbbell + yaw_dumbbell + total_accel_dumbbell + gyros_dumbbell_x +
                  gyros_dumbbell_y + gyros_dumbbell_z +  magnet_dumbbell_z + roll_forearm +
                  pitch_forearm + yaw_forearm + total_accel_forearm + gyros_forearm_x +
                  gyros_forearm_y + gyros_forearm_z +  accel_forearm_x + accel_forearm_z +
                  magnet_forearm_x + magnet_forearm_y +
                  magnet_forearm_z, data=training_blanks_cv_sample,
                     method="rf", preProcess=c("scale","center"),
                     trControl=TcontrolTS, na.action=na.pass)
print(modelTScv2rf)
```

```
## Random Forest
##
## 500 samples
##  34 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (34), centered (34)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 450, 450, 450, 450, 450, 450, ...
## Resampling results across tuning parameters:
##
##   mtry  Accuracy  Kappa
##    2    0.818     0.7725
##   18    0.806     0.7575
##   34    0.798     0.7475
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 2.
```

```r
importanceTSCV2rf <- varImp(modelTScv2rf, scale=TRUE)
print(importanceTSCV2rf)
```

```
## rf variable importance
##
##   only 20 most important variables shown (out of 34)
##
##                      Overall
## pitch_forearm         100.00
## magnet_belt_z          84.32
## magnet_dumbbell_z      77.00
## magnet_belt_y          75.31
## roll_dumbbell          75.08
## yaw_belt               71.88
## accel_belt_z           69.76
## accel_forearm_x        63.67
## pitch_belt             59.68
## magnet_arm_y           48.61
## pitch_dumbbell         43.33
## magnet_forearm_x       43.05
## gyros_dumbbell_y       39.39
## roll_forearm           37.42
## total_accel_dumbbell   37.01
## yaw_dumbbell           36.01
## yaw_arm                30.14
## gyros_belt_z           30.13
## magnet_belt_x          28.21
## roll_arm               26.74
```

- Decision Trees

```r
modelTScv2C50 <- train(factor(classe) ~ pitch_belt + yaw_belt + gyros_belt_x +
                  gyros_belt_y + gyros_belt_z +
                  magnet_belt_y + magnet_belt_z + roll_arm + pitch_arm + yaw_arm +
                  accel_belt_y + accel_belt_z + magnet_belt_x +  magnet_arm_y + roll_dumbbell +
                  pitch_dumbbell + yaw_dumbbell + total_accel_dumbbell + gyros_dumbbell_x +
                  gyros_dumbbell_y + gyros_dumbbell_z +  magnet_dumbbell_z + roll_forearm +
                  pitch_forearm + yaw_forearm + total_accel_forearm + gyros_forearm_x +
                  gyros_forearm_y + gyros_forearm_z +  accel_forearm_x + accel_forearm_z +
                  magnet_forearm_x + magnet_forearm_y +
                  magnet_forearm_z, data=training_blanks_cv_sample,
                      method="C5.0", preProcess=c("scale","center"),
                      trControl=TcontrolTS, na.action=na.pass)
print(modelTScv2C50)
```

```
## C5.0
##
## 500 samples
##  34 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (34), centered (34)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 450, 450, 450, 450, 450, 450, ...
## Resampling results across tuning parameters:
```

```
##
##   model  winnow  trials  Accuracy  Kappa
##   rules  FALSE    1      0.622     0.5275
##   rules  FALSE   10      0.744     0.6800
##   rules  FALSE   20      0.780     0.7250
##   rules   TRUE    1      0.628     0.5350
##   rules   TRUE   10      0.742     0.6775
##   rules   TRUE   20      0.782     0.7275
##   tree   FALSE    1      0.650     0.5625
##   tree   FALSE   10      0.766     0.7075
##   tree   FALSE   20      0.782     0.7275
##   tree    TRUE    1      0.656     0.5700
##   tree    TRUE   10      0.756     0.6950
##   tree    TRUE   20      0.780     0.7250
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were trials = 20, model = rules
##  and winnow = TRUE.
```

```
importanceTSCV2C50 <- varImp(modelTScv2C50, scale=TRUE)
print(importanceTSCV2C50)
```

```
## C5.0 variable importance
##
##   only 20 most important variables shown (out of 34)
##
##                        Overall
## roll_dumbbell            100.0
## yaw_arm                  100.0
## accel_forearm_x          100.0
## magnet_belt_z            100.0
## yaw_belt                 100.0
## pitch_forearm            100.0
## accel_belt_z             100.0
## magnet_belt_y            100.0
## gyros_belt_z              99.8
## total_accel_dumbbell      99.8
## roll_forearm              96.6
## pitch_belt                96.0
## gyros_dumbbell_y          94.6
## magnet_arm_y              92.0
## roll_arm                  90.0
## gyros_belt_x              89.4
## yaw_dumbbell              87.0
## magnet_forearm_y          83.4
## accel_forearm_z           77.4
## gyros_forearm_y           74.8
```

- Bagged Trees

```
modelTScv2treebag <- train(factor(classe) ~ pitch_belt + yaw_belt + gyros_belt_x +
                  gyros_belt_y + gyros_belt_z +
                  magnet_belt_y + magnet_belt_z + roll_arm + pitch_arm + yaw_arm +
                  accel_belt_y + accel_belt_z + magnet_belt_x +  magnet_arm_y + roll_dumbbell +
                  pitch_dumbbell + yaw_dumbbell + total_accel_dumbbell + gyros_dumbbell_x +
                  gyros_dumbbell_y + gyros_dumbbell_z +  magnet_dumbbell_z + roll_forearm +
```

```r
                 pitch_forearm + yaw_forearm + total_accel_forearm + gyros_forearm_x +
                 gyros_forearm_y + gyros_forearm_z +  accel_forearm_x + accel_forearm_z +
                 magnet_forearm_x + magnet_forearm_y +
                 magnet_forearm_z, data=training_blanks_cv_sample,
                        method="treebag", preProcess=c("scale","center"),
                        trControl=TcontrolTS, na.action=na.pass)
print(modelTScv2treebag)
```

```
## Bagged CART
##
## 500 samples
##  34 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (34), centered (34)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 450, 450, 450, 450, 450, 450, ...
## Resampling results:
##
##   Accuracy  Kappa
##   0.754     0.6925
```

```r
importanceTSCV2treebag <- varImp(modelTScv2treebag, scale=TRUE)
print(importanceTSCV2treebag)
```

```
## treebag variable importance
##
##   only 20 most important variables shown (out of 34)
##
##                      Overall
## magnet_belt_z         100.00
## pitch_forearm          98.19
## yaw_belt               76.22
## magnet_dumbbell_z      75.69
## magnet_belt_y          68.64
## pitch_belt             63.89
## roll_dumbbell          61.36
## accel_belt_z           46.16
## accel_forearm_x        43.95
## gyros_belt_z           36.34
## magnet_arm_y           34.45
## gyros_dumbbell_y       33.55
## yaw_arm                27.22
## yaw_dumbbell           26.59
## roll_arm               23.81
## gyros_belt_x           23.46
## pitch_dumbbell         22.49
## gyros_forearm_z        20.60
## total_accel_dumbbell   19.91
## roll_forearm           19.53
```

- SVM Polynomial Kernel

```r
modelTScv2svmPoly <- train(factor(classe) ~ pitch_belt + yaw_belt + gyros_belt_x +
                 gyros_belt_y + gyros_belt_z +
```

```r
                  magnet_belt_y + magnet_belt_z + roll_arm + pitch_arm + yaw_arm +
                  accel_belt_y + accel_belt_z + magnet_belt_x +  magnet_arm_y + roll_dumbbell +
                  pitch_dumbbell + yaw_dumbbell + total_accel_dumbbell + gyros_dumbbell_x +
                  gyros_dumbbell_y + gyros_dumbbell_z +  magnet_dumbbell_z + roll_forearm +
                  pitch_forearm + yaw_forearm + total_accel_forearm + gyros_forearm_x +
                  gyros_forearm_y + gyros_forearm_z +  accel_forearm_x + accel_forearm_z +
                  magnet_forearm_x + magnet_forearm_y +
                  magnet_forearm_z, data=training_blanks_cv_sample,
                          method="svmPoly", preProcess=c("scale","center"),
                          trControl=TcontrolTS, na.action=na.pass)
print(modelTScv2svmPoly)
```

```
## Support Vector Machines with Polynomial Kernel
##
## 500 samples
##  34 predictor
##   5 classes: 'A', 'B', 'C', 'D', 'E'
##
## Pre-processing: scaled (34), centered (34)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 450, 450, 450, 450, 450, 450, ...
## Resampling results across tuning parameters:
##
##   degree  scale  C     Accuracy  Kappa
##   1       0.001  0.25  0.360     0.2000
##   1       0.001  0.50  0.360     0.2000
##   1       0.001  1.00  0.360     0.2000
##   1       0.010  0.25  0.384     0.2300
##   1       0.010  0.50  0.422     0.2775
##   1       0.010  1.00  0.436     0.2950
##   1       0.100  0.25  0.490     0.3625
##   1       0.100  0.50  0.518     0.3975
##   1       0.100  1.00  0.552     0.4400
##   2       0.001  0.25  0.362     0.2025
##   2       0.001  0.50  0.362     0.2025
##   2       0.001  1.00  0.376     0.2200
##   2       0.010  0.25  0.440     0.3000
##   2       0.010  0.50  0.484     0.3550
##   2       0.010  1.00  0.534     0.4175
##   2       0.100  0.25  0.722     0.6525
##   2       0.100  0.50  0.718     0.6475
##   2       0.100  1.00  0.702     0.6275
##   3       0.001  0.25  0.366     0.2075
##   3       0.001  0.50  0.366     0.2075
##   3       0.001  1.00  0.392     0.2400
##   3       0.010  0.25  0.496     0.3700
##   3       0.010  0.50  0.568     0.4600
##   3       0.010  1.00  0.636     0.5450
##   3       0.100  0.25  0.710     0.6375
##   3       0.100  0.50  0.706     0.6325
##   3       0.100  1.00  0.708     0.6350
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were degree = 2, scale = 0.1 and C
```

```
##  = 0.25.
```

```r
importanceTSCV2svmPoly <- varImp(modelTScv2svmPoly, scale=TRUE)
print(importanceTSCV2svmPoly)
```

```
## ROC curve variable importance
##
##   variables are sorted by maximum importance across the classes
##   only 20 most important variables shown (out of 34)
##
##                         A       B      C     D      E
## pitch_forearm       70.19 100.000 70.193 70.19 100.00
## accel_forearm_x     33.32  89.116 41.148 25.94  89.12
## magnet_arm_y        22.99  69.432 78.901 22.99  69.43
## magnet_forearm_x    46.03  71.411 39.991 23.88  71.41
## magnet_dumbbell_z   55.72  16.974 70.391 44.88  55.72
## pitch_dumbbell      52.53  56.995 52.535 63.45  56.99
## magnet_belt_y       29.61  29.609 61.227 29.61  22.80
## pitch_arm           18.89  38.864 56.873 18.60  38.86
## roll_dumbbell       47.91  45.349 25.392 52.95  47.91
## magnet_belt_z       12.57  12.574 46.978 12.57  11.30
## roll_arm            44.24  44.238 44.238 44.24  22.38
## yaw_dumbbell        35.64  35.637 35.637 40.33  22.36
## yaw_forearm         31.13  39.930 31.131 31.13  39.93
## magnet_belt_x       35.41  35.409 35.409 39.55  16.71
## total_accel_forearm 19.29  18.374 38.240 13.91  19.29
## magnet_forearm_y    21.49  34.282 35.546 34.34  34.28
## total_accel_dumbbell 18.83  18.831 32.075 19.70  11.08
## roll_forearm        30.02   4.034  3.532 24.49  30.02
## accel_belt_z        28.92  28.924 28.924 28.92  26.91
## pitch_belt          17.90  17.902 22.134 28.47  15.38
```

We resample the accuracy and kappa of the four models for the least correlated predictors using resampled training data as mock test data.

```r
allModelscv2 <- resamples(list(SVMPoly=modelTScv2svmPoly,
                               DecisionTree=modelTScv2C50,
                               RandomForest=modelTScv2rf,
                               BaggedTrees=modelTScv2treebag
))
summary(allModelscv2)
```

```
##
## Call:
## summary.resamples(object = allModelscv2)
##
## Models: SVMPoly, DecisionTree, RandomForest, BaggedTrees
## Number of resamples: 10
##
## Accuracy
##              Min. 1st Qu. Median  Mean 3rd Qu. Max. NA's
## SVMPoly      0.66   0.700   0.72 0.722   0.735 0.80    0
## DecisionTree 0.66   0.745   0.78 0.782   0.800 0.92    0
## RandomForest 0.74   0.785   0.83 0.818   0.855 0.88    0
## BaggedTrees  0.66   0.710   0.75 0.754   0.775 0.90    0
##
```

```
## Kappa
##                   Min. 1st Qu. Median   Mean 3rd Qu.  Max. NA's
## SVMPoly      0.575 0.62500 0.6500 0.6525 0.66875 0.750    0
## DecisionTree 0.575 0.68125 0.7250 0.7275 0.75000 0.900    0
## RandomForest 0.675 0.73125 0.7875 0.7725 0.81875 0.850    0
## BaggedTrees  0.575 0.63750 0.6875 0.6925 0.71875 0.875    0
```