

Machine Learning Modeling of Selected Weight-lifting Activities

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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 weight-lifting exercise incorrectly. Sequences B, C, D, and E are specific ways to perform the weight-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 files, 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 assess 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 assess 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.

```
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)

```

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.

```
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 exploratory 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 accurate 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.

```

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_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", "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$class, 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.

```
set.seed(22)
```

```
predictors(resultsTS)
```

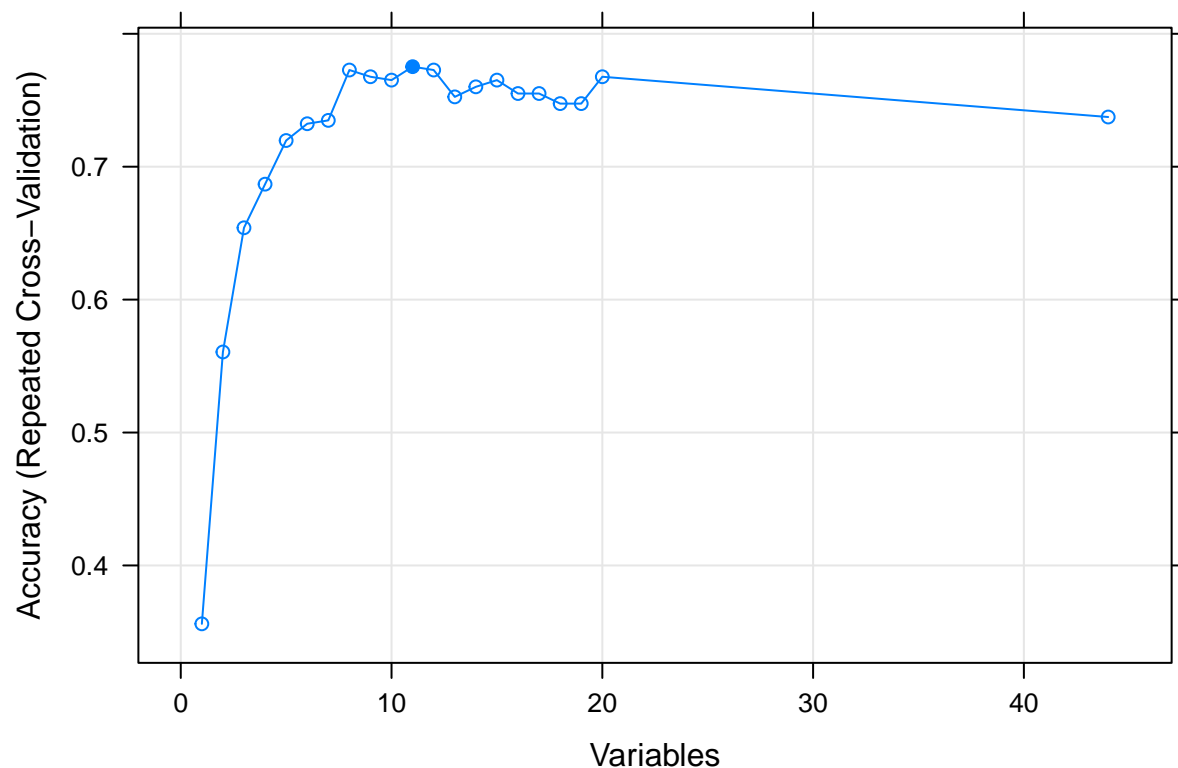
```
## [1] "roll_belt"          "magnet_dumbbell_y" "magnet_dumbbell_z"
```

```
## [4] "pitch_forearm"      "magnet_belt_y"     "roll_dumbbell"
```

```
## [7] "yaw_belt"           "roll_forearm"      "magnet_belt_z"
```

```
## [10] "accel_dumbbell_y"   "accel_belt_z"
```

```
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).

```

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.

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.

```
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
```

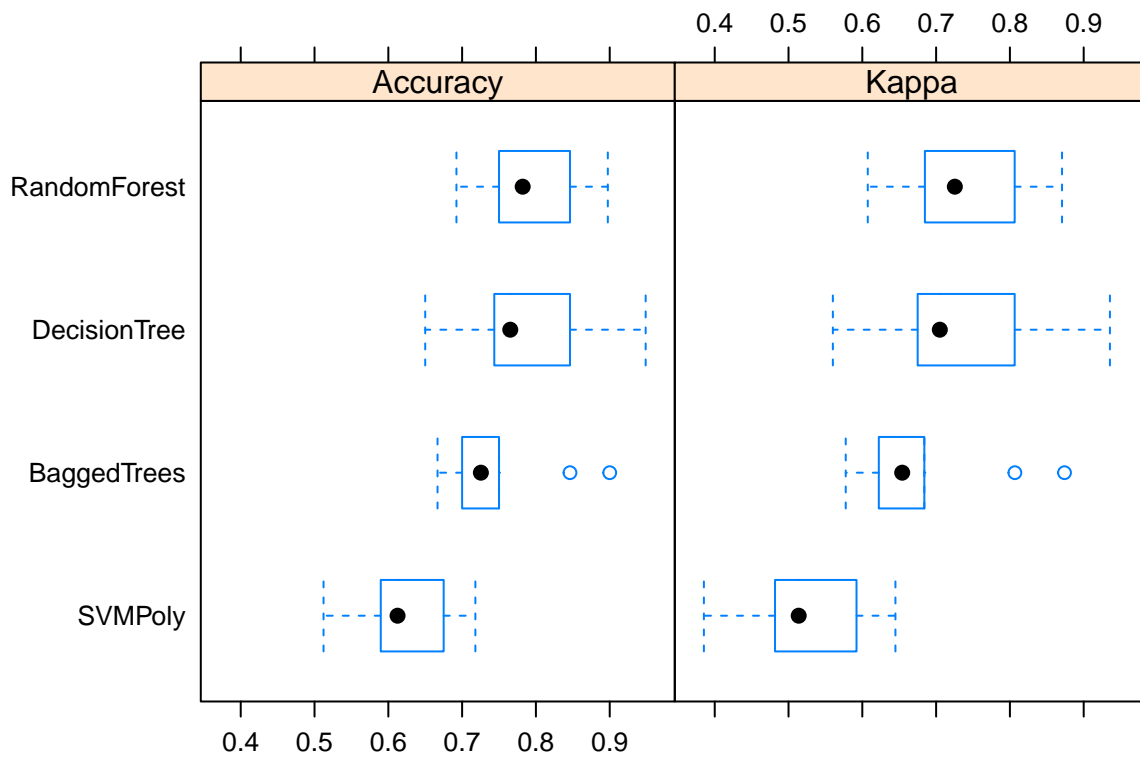
We resample the accuracy and kappa of the four models for all predictors.

```
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.

```
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 out 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)
modelTSselfrf <- 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(modelTSselfrf)

## 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.

importanceTSselfrf <- varImp(modelTSselfrf, scale=TRUE)
print(importanceTSselfrf)

## 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_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="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.

```
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).

```
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
```

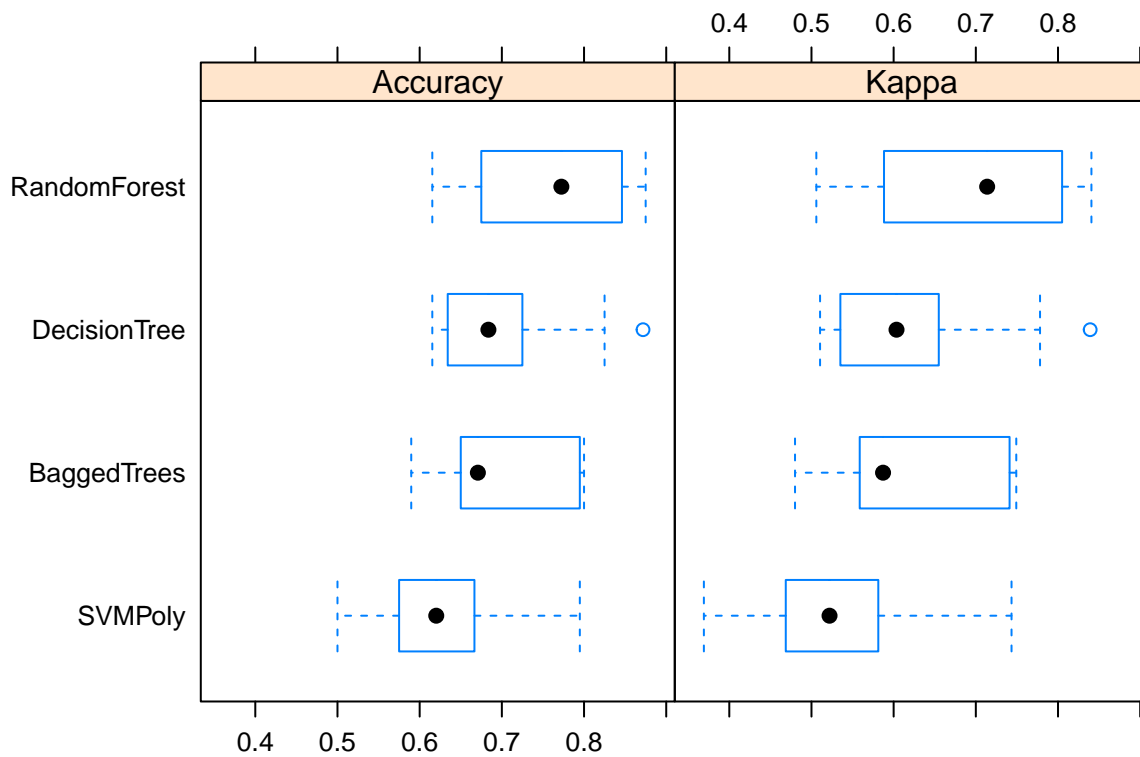
We resample the accuracy and kappa of the four models for the least correlated predictors.

```
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.

```
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

	predictself	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.

```

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

```

```

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.

```

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
```

```
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

```
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.

```
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.

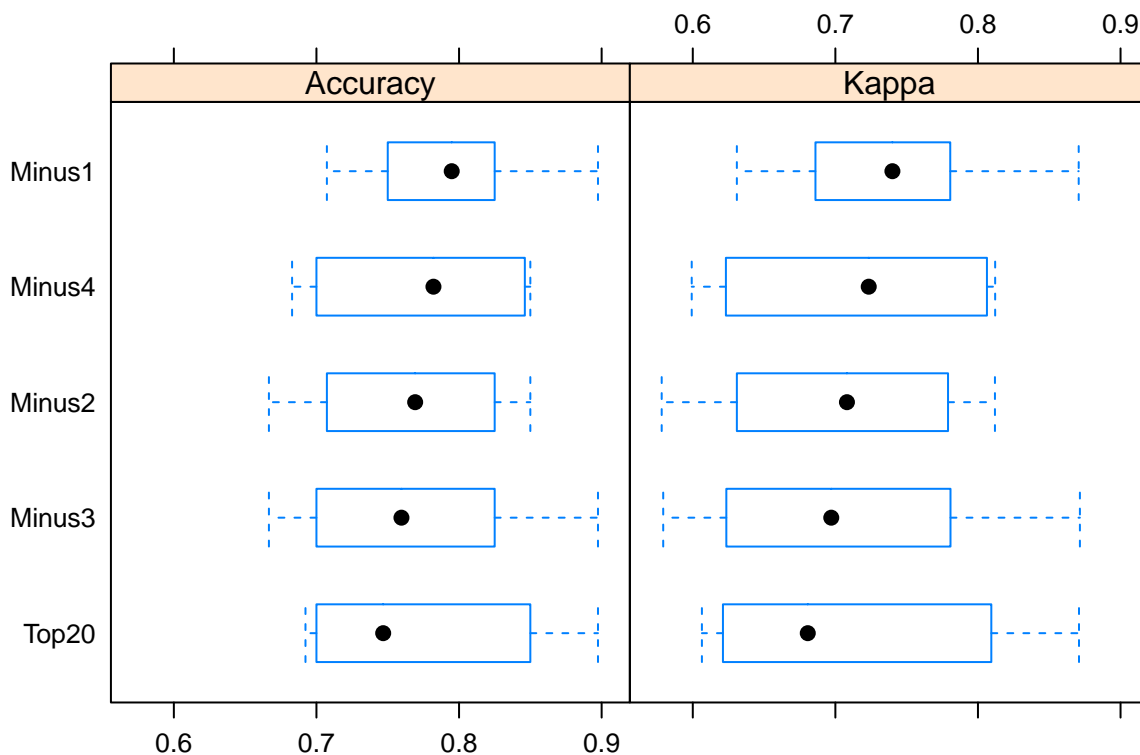
```
set.seed(22)
allModelsselminus <- resamples(list(Top20=modelTSselrftop20,
  Minus1=modelTSselrfminus1,
  Minus2=modelTSselrfminus2,
  Minus3=modelTSselrfminus3,
  Minus4=modelTSselrfminus4
))
summary(allModelsselminus)
```

```
##
## 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))

```

```

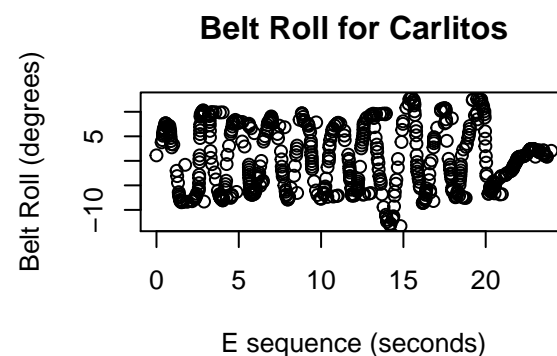
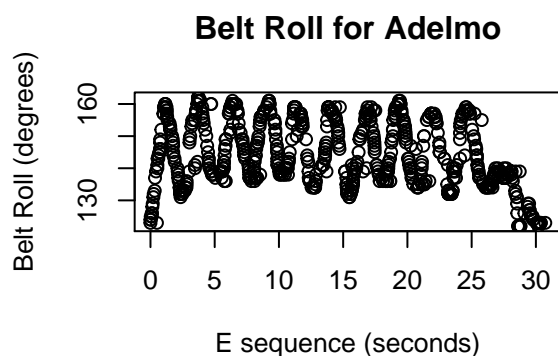
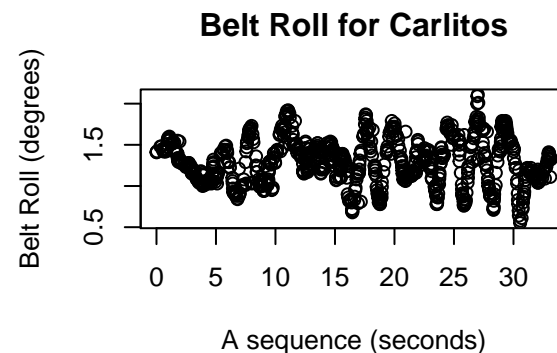
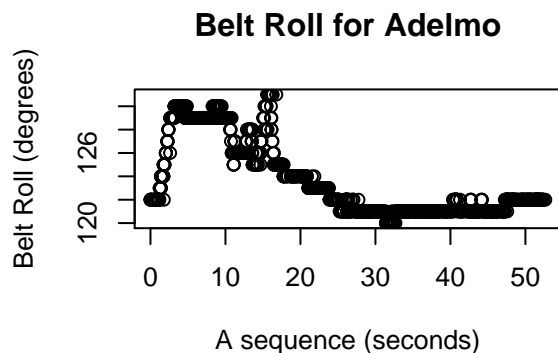
trg_data_jeremy_D_left <- mutate(trg_jeremy_D, time_left = rel_time - min(rel_time))
trg_data_jeremy_E_left <- mutate(trg_jeremy_E, time_left = rel_time - min(rel_time))

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

```
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", "cvt_d_timestamp",
  "new_window", "num_window", "kurtosis_roll_belt", "kurtosis_pitch_belt",
  "skewness_roll_belt",
  "skewness_roll_belt.1", "max_roll_belt", "max_pitch_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_pitch_arm",
  "kurtosis_yaw_arm", "skewness_roll_arm", "skewness_pitch_arm", "skewness_yaw_arm",
  "max_roll_arm", "max_pitch_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_pitch_dumbbell",
  "skewness_roll_dumbbell", "skewness_pitch_dumbbell",
  "max_roll_dumbbell", "max_pitch_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_pitch_forearm",
  "skewness_roll_forearm", "skewness_pitch_forearm",
  "max_roll_forearm", "max_pitch_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.

```
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_pitch_arm",
"kurtosis_yaw_arm", "skewness_roll_arm", "skewness_pitch_arm", "skewness_yaw_arm",
"max_yaw_arm", "min_yaw_arm", "kurtosis_pitch_dumbbell",
"skewness_roll_dumbbell", "skewness_pitch_dumbbell",
"max_roll_dumbbell", "max_pitch_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_pitch_forearm",
"skewness_roll_forearm", "skewness_pitch_forearm",
"max_pitch_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 reducing 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).

```
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_pitch_dumbbell"
## [11] "max_roll_dumbbell"  "avg_roll_forearm"
## [13] "total_accel_dumbbell" "avg_roll_arm"
## [15] "var_pitch_forearm"  "min_roll_dumbbell"
## [17] "max_pitch_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).

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

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

```
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_pitch_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_pitch_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.

```
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.
```

```
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_pitch_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
```

```
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_pitch_dumbbell 20.047
## var_pitch_belt 18.639
## avg_pitch_dumbbell 14.347
## var_yaw_belt 12.704
## max_pitch_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
```

```
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.

```
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

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_pitch_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
```

```
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.

```
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 using the RFE algorithm.

```
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
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

```
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, ...
## 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.
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

```
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.
```

```
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

```
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 +
```

```

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

```

```

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

```

modelTScv2svmPoly <- 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="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.
```

```
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.

```
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
```