Practical Machine Learning Project

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Project Background

Using devices such as Jawbone Up, Nike FuelBand, and Fitbit it is now possible to collect a large amount of data about personal activity relatively inexpensively. These type of devices are part of the quantified self movement – a group of enthusiasts who take measurements about themselves regularly to improve their health, to find patterns in their behavior, or because they are tech geeks. One thing that people regularly do is quantify how much of a particular activity they do, but they rarely quantify how well they do it. In this project, your goal will be to use data from accelerometers on the belt, forearm, arm, and dumbell of 6 participants. They were asked to perform barbell lifts correctly and incorrectly in 5 different ways. More information is available from the website here: http://web.archive.org/web/20161224072740/http:/groupware.les.inf.puc-rio.br/har (see the section on the Weight Lifting Exercise Dataset).

The training data for this project are available here: https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv

The test data are available here: https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv

The data for this project come from this source: http://web.archive.org/web/20161224072740/http:/groupware.les.inf.puc-rio.br/har. If you use the document you create for this class for any purpose please cite them as they have been very generous in allowing their data to be used for this kind of assignment.

The goal of your project is to predict the manner in which they did the exercise. This is the "classe" variable in the training set. You may use any of the other variables to predict with. You should create a report describing how you built your model, how you used cross validation, what you think the expected out of sample error is, and why you made the choices you did. You will also use your prediction model to predict 20 different test cases.

Loading Libraries

We first upload the libraries we need to perform the analysis and create the prediction model.

```r
library(knitr)
library(caret)
```

```
## Warning: package 'caret' was built under R version 3.6.2
```

```
## Loading required package: lattice
```

```
## Loading required package: ggplot2
```

```r
library(rpart)
library(rpart.plot)
```

```
## Warning: package 'rpart.plot' was built under R version 3.6.2
```

```r
library(rattle)
```

```
## Warning: package 'rattle' was built under R version 3.6.2
```

```
## Rattle: A free graphical interface for data science with R.
## Version 5.3.0 Copyright (c) 2006-2018 Togaware Pty Ltd.
## Type 'rattle()' to shake, rattle, and roll your data.
```

```r
library(randomForest)
```

```
## Warning: package 'randomForest' was built under R version 3.6.2
## randomForest 4.6-14
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
## The following object is masked from 'package:rattle':
##
##     importance
## The following object is masked from 'package:ggplot2':
##
##     margin
```

```r
library(corrplot)
```

```
## Warning: package 'corrplot' was built under R version 3.6.2
## corrplot 0.84 loaded
```

```r
library(gbm)
```

```
## Warning: package 'gbm' was built under R version 3.6.2
## Loaded gbm 2.1.5
```

```r
set.seed(12345)
```

Loading Data and Cleaning

Next we load the dataset using the URLs provided and partition the data into a training and a test dataset.

```r
# set the URL for the download
UrlTrain <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
UrlTest  <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"

# download the datasets
training <- read.csv(url(UrlTrain))
testing  <- read.csv(url(UrlTest))

# create a partition with the training dataset
inTrain  <- createDataPartition(training$classe, p=0.7, list=FALSE)
TrainSet <- training[inTrain, ]
TestSet  <- training[-inTrain, ]
dim(TrainSet)
```

```
## [1] 13737   160
```

```r
dim(TestSet)
```

```
## [1] 5885  160
```

Both datasets have 160 variables. Next we will remove variables with Near Zero Variance (NZV) and those that are mostly NA.

```r
# remove variables with Nearly Zero Variance
NZV <- nearZeroVar(TrainSet)
```

```
TrainSet <- TrainSet[, -NZV]
TestSet  <- TestSet[, -NZV]
dim(TrainSet)
```

```
## [1] 13737   104
```

```
dim(TestSet)
```

```
## [1] 5885  104
```

```
# remove variables that are mostly NA
AllNA    <- sapply(TrainSet, function(x) mean(is.na(x))) > 0.95
TrainSet <- TrainSet[, AllNA==FALSE]
TestSet  <- TestSet[, AllNA==FALSE]
dim(TrainSet)
```

```
## [1] 13737    59
```

```
dim(TestSet)
```

```
## [1] 5885   59
```

```
# remove identification only variables (columns 1 to 5)
TrainSet <- TrainSet[, -(1:5)]
TestSet  <- TestSet[, -(1:5)]
dim(TrainSet)
```

```
## [1] 13737    54
```

```
dim(TestSet)
```

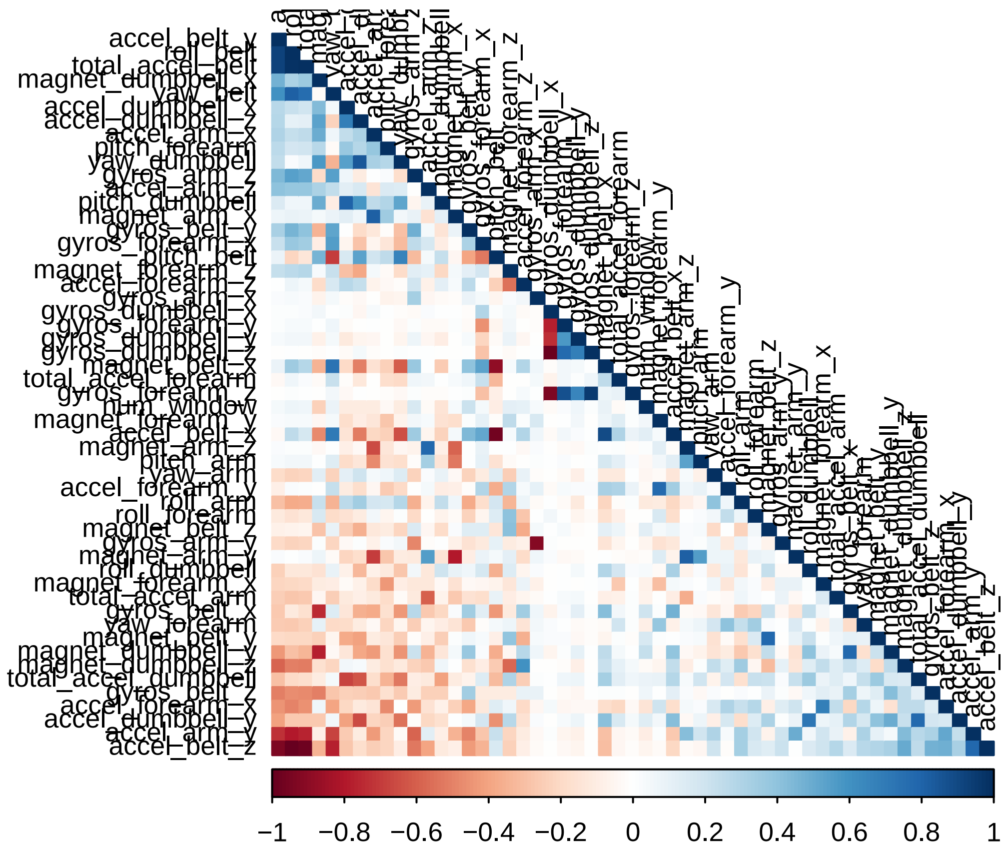
```
## [1] 5885   54
```

After performing the above, there are now only 54 variables.

Exploratory Analysis

Before starting the modeling, we will look at correlation among the variables.

```
corMatrix <- cor(TrainSet[, -54])
corrplot(corMatrix, order = "FPC", method = "color", type = "lower",
         tl.cex = 0.8, tl.col = rgb(0, 0, 0))
```



Highly correlated variables are in dark colors. Since the correlations are so few, we do not need to perform Principle Component Analysis (PCA).

Next, we will apply three different methods (random forests, decision trees, and generalized boosted model) to the training dataset to model the regressions and the most accurate model when applied to the test dataset will be used later. A confusion matrix will be plotted at the end of each method to visualize the accuracy of each one.

Random Forest Method

```
# model fit
set.seed(12345)
controlRF <- trainControl(method="cv", number=3, verboseIter=FALSE)
modFitRandForest <- train(classe ~ ., data=TrainSet, method="rf",
                          trControl=controlRF)
modFitRandForest$finalModel
```

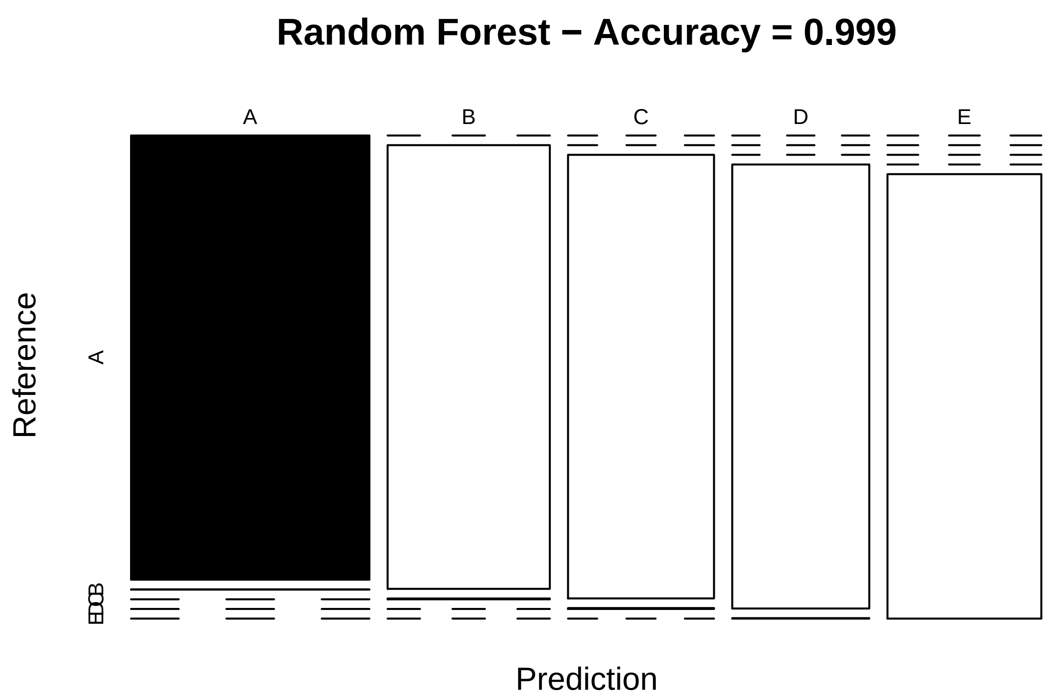
```
##
## Call:
##  randomForest(x = x, y = y, mtry = param$mtry)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 27
##
##         OOB estimate of  error rate: 0.23%
## Confusion matrix:
##      A    B    C    D    E  class.error
```

```
## A 3904    2    0    0    0 0.0005120328
## B    6 2647    4    1    0 0.0041384500
## C    0    5 2391    0    0 0.0020868114
## D    0    0    9 2243    0 0.0039964476
## E    0    0    0    5 2520 0.0019801980
```

```r
# prediction on test dataset
predictRandForest <- predict(modFitRandForest, newdata=TestSet)
confMatRandForest <- confusionMatrix(predictRandForest, TestSet$classe)
confMatRandForest
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1674    1    0    0    0
##          B    0 1138    2    0    0
##          C    0    0 1024    2    0
##          D    0    0    0  962    1
##          E    0    0    0    0 1081
##
## Overall Statistics
##
##                Accuracy : 0.999
##                  95% CI : (0.9978, 0.9996)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9987
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   0.9991   0.9981   0.9979   0.9991
## Specificity            0.9998   0.9996   0.9996   0.9998   1.0000
## Pos Pred Value         0.9994   0.9982   0.9981   0.9990   1.0000
## Neg Pred Value         1.0000   0.9998   0.9996   0.9996   0.9998
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2845   0.1934   0.1740   0.1635   0.1837
## Detection Prevalence   0.2846   0.1937   0.1743   0.1636   0.1837
## Balanced Accuracy      0.9999   0.9994   0.9988   0.9989   0.9995
```

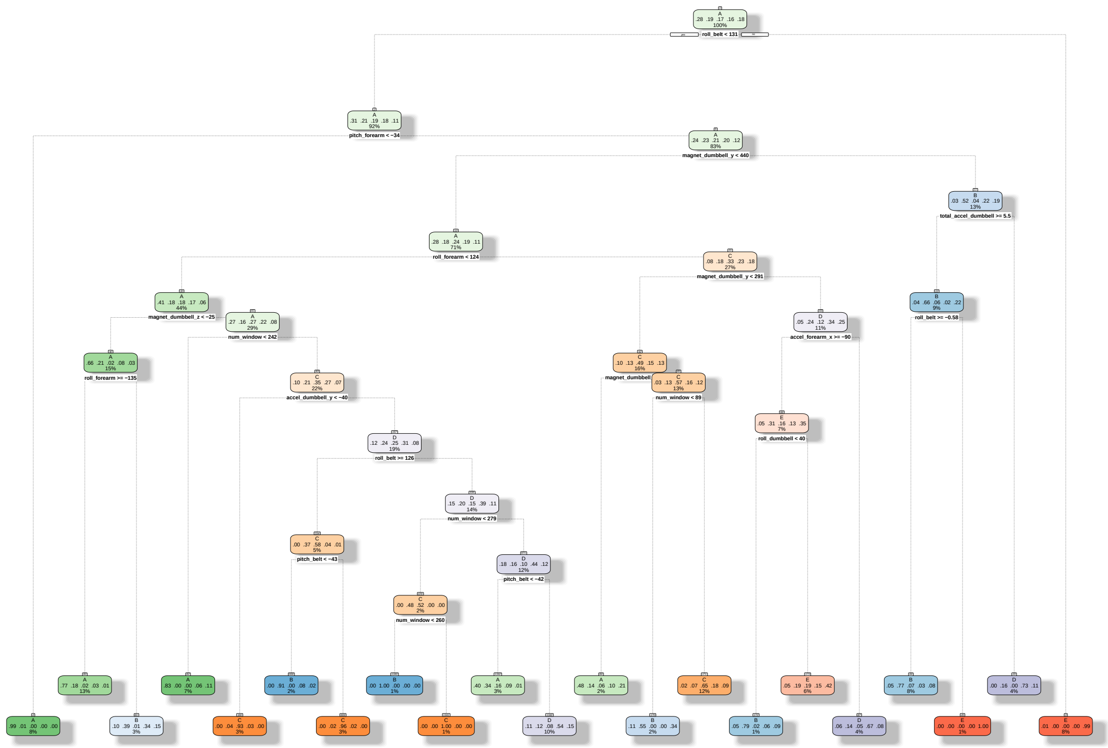
```r
# plot matrix results
plot(confMatRandForest$table, col = confMatRandForest$byClass,
     main = paste("Random Forest - Accuracy =",
                  round(confMatRandForest$overall['Accuracy'], 4)))
```



Decision Trees Method

```
# model fit
set.seed(12345)
modFitDecTree <- rpart(classe ~ ., data=TrainSet, method="class")
fancyRpartPlot(modFitDecTree)
```

```
## Warning: labs do not fit even at cex 0.15, there may be some overplotting
```



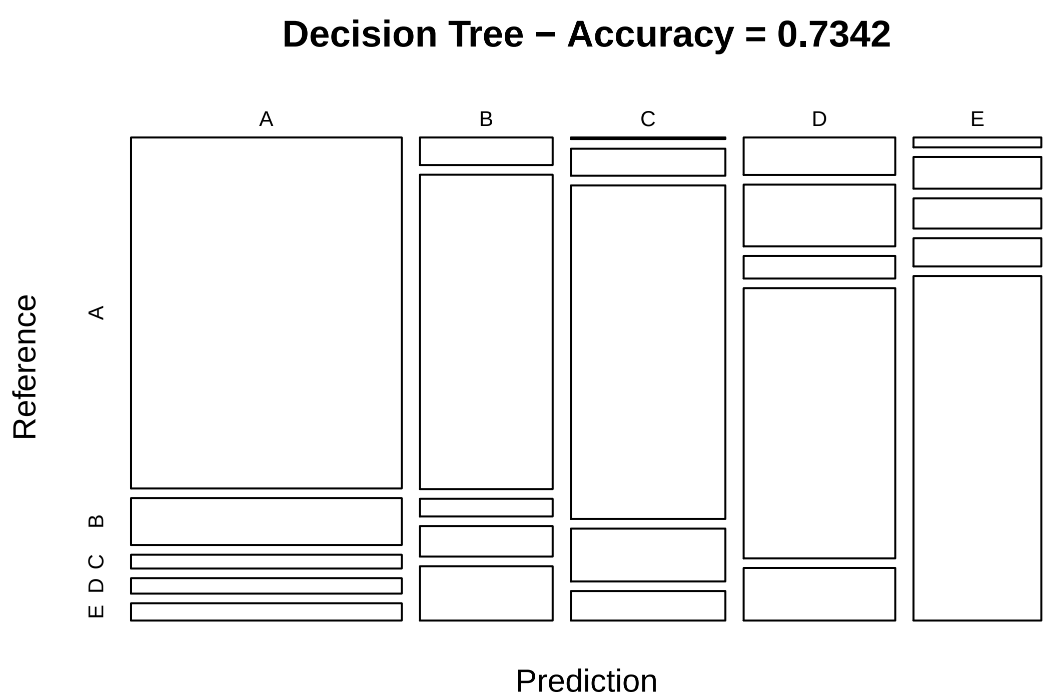
Rattle 2020−Jan−13 17:46:34 stefa

```r
# prediction on test dataset
predictDecTree <- predict(modFitDecTree, newdata=TestSet, type="class")
confMatDecTree <- confusionMatrix(predictDecTree, TestSet$classe)
confMatDecTree
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1502  201   59   66   74
##          B   58  660   37   64  114
##          C    4   66  815  129   72
##          D   90  148   54  648  126
##          E   20   64   61   57  696
##
## Overall Statistics
##
##                Accuracy : 0.7342
##                  95% CI : (0.7228, 0.7455)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.6625
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
```

```
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.8973   0.5795   0.7943   0.6722   0.6433
## Specificity            0.9050   0.9425   0.9442   0.9151   0.9579
## Pos Pred Value         0.7897   0.7074   0.7505   0.6079   0.7751
## Neg Pred Value         0.9568   0.9033   0.9560   0.9344   0.9226
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2552   0.1121   0.1385   0.1101   0.1183
## Detection Prevalence   0.3232   0.1585   0.1845   0.1811   0.1526
## Balanced Accuracy      0.9011   0.7610   0.8693   0.7936   0.8006
```

```r
# plot matrix results
plot(confMatDecTree$table, col = confMatDecTree$byClass,
     main = paste("Decision Tree - Accuracy =",
                  round(confMatDecTree$overall['Accuracy'], 4)))
```



Generalized Boosted Model Method

```r
# model fit
set.seed(12345)
controlGBM <- trainControl(method = "repeatedcv", number = 5, repeats = 1)
modFitGBM  <- train(classe ~ ., data=TrainSet, method = "gbm",
                    trControl = controlGBM, verbose = FALSE)
modFitGBM$finalModel
```

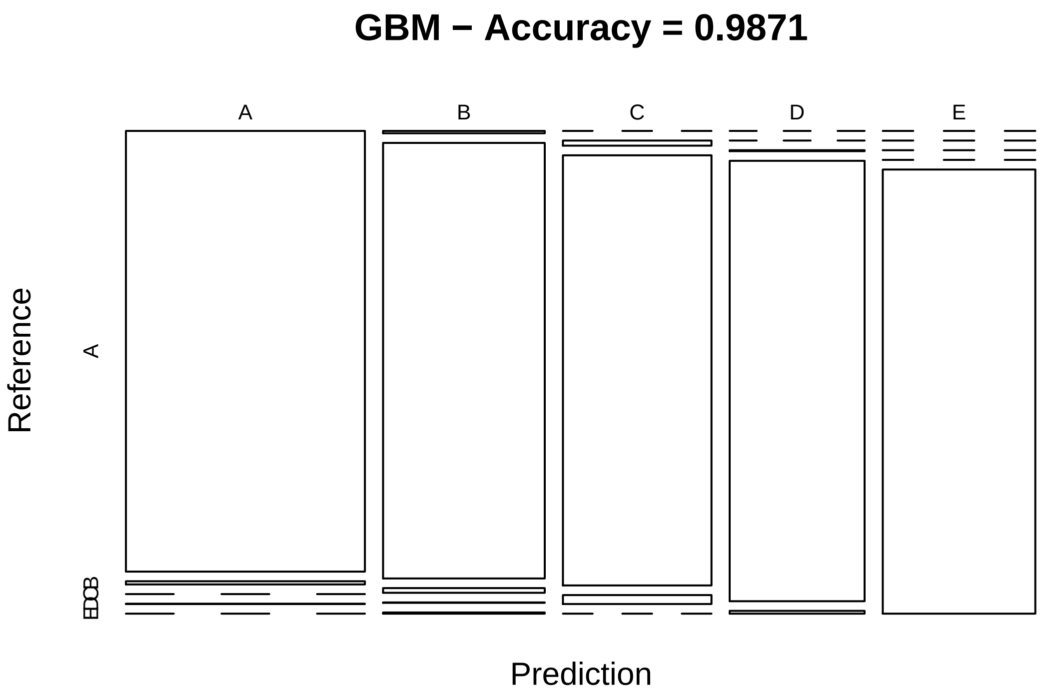
```
## A gradient boosted model with multinomial loss function.
## 150 iterations were performed.
```

```
## There were 53 predictors of which 53 had non-zero influence.
```

```r
# prediction on test dataset
predictGBM <- predict(modFitGBM, newdata=TestSet)
confMatGBM <- confusionMatrix(predictGBM, TestSet$classe)
confMatGBM
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1668   12    0    1    0
##          B    6 1115   12    1    3
##          C    0   12 1012   21    0
##          D    0    0    2  941    6
##          E    0    0    0    0 1073
##
## Overall Statistics
##
##                Accuracy : 0.9871
##                  95% CI : (0.9839, 0.9898)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9837
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9964   0.9789   0.9864   0.9761   0.9917
## Specificity            0.9969   0.9954   0.9932   0.9984   1.0000
## Pos Pred Value         0.9923   0.9807   0.9684   0.9916   1.0000
## Neg Pred Value         0.9986   0.9949   0.9971   0.9953   0.9981
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2834   0.1895   0.1720   0.1599   0.1823
## Detection Prevalence   0.2856   0.1932   0.1776   0.1613   0.1823
## Balanced Accuracy      0.9967   0.9871   0.9898   0.9873   0.9958
```

```r
# plot matrix results
plot(confMatGBM$table, col = confMatGBM$byClass,
     main = paste("GBM - Accuracy =", round(confMatGBM$overall['Accuracy'], 4)))
```



Applied to Test Data

The accuracy of the three methods are: _____ for Random Forest, _____ for Decision Trees, and _____ for GBM. Since the Random Forest model was most accurate, it will be used for the project prediction quiz below.

```
predictTEST <- predict(modFitRandForest, newdata=testing)
predictTEST
```

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