# Machine Learning Course Project

This report attempts to predict type of exercise based on a total of 157 possible predictor variables.

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

## Warning: Failed to load RGtk2 dynamic library, attempting to install it.

## Please install GTK+ from http://r.research.att.com/libs/GTK_2.24.17-X11.pkg
## If the package still does not load, please ensure that GTK+ is installed and that it is on your PATH
## IN ANY CASE, RESTART R BEFORE TRYING TO LOAD THE PACKAGE AGAIN
## Rattle: A free graphical interface for data mining with R.
## Version 4.0.0 Copyright (c) 2006-2015 Togaware Pty Ltd.
## Type 'rattle()' to shake, rattle, and roll your data.
## randomForest 4.6-12
## Type rfNews() to see new features/changes/bug fixes.
```

Next, an examination of the predictor variables was made to determine which could easily be excluded from the model based on having no variation. From this we can remove 60 of the variables. Based on this information we then create a new training data set that removes these variables, leaving 97 possible predictors.

```r
nzv <- nearZeroVar(pml.training)
filterPML.training <-pml.training[,-nzv]
dim(filterPML.training)
```

```
## [1] 19622   100
```

The first variable is useless as it is just an ID number, so is the name of the person so we want to remove these.

```r
MyTraining <- filterPML.training[c(-1)]
```

```r
MyTraining <- MyTraining[c(-1)]
dim(MyTraining)
```

```
## [1] 19622    98
```

We also need to remove the NA values. We set a threshold of 50% - if more than 50% of the column includes NA values we want to remove them from the possible set of predictors.

```r
trainingNoNA <- MyTraining
```

```r
for(i in 1:length(MyTraining)) {
  if( sum( is.na( MyTraining[, i] ) ) /nrow(MyTraining) >= .5 ) {
    for(j in 1:length(trainingNoNA)) {
      if( length( grep(names(MyTraining[i]), names(trainingNoNA)[j]) ) ==1) {
        trainingNoNA <- trainingNoNA[ , -j]
      }
    }
  }
}
```

```r
dim(trainingNoNA)
```

```
## [1] 19622    57
```

Now we have a possible 56 predictors (57-our classe variable to be predicted).

Because the testing set is reserved for the ultimate course test, we split the training data into a training and testing set that we can use.

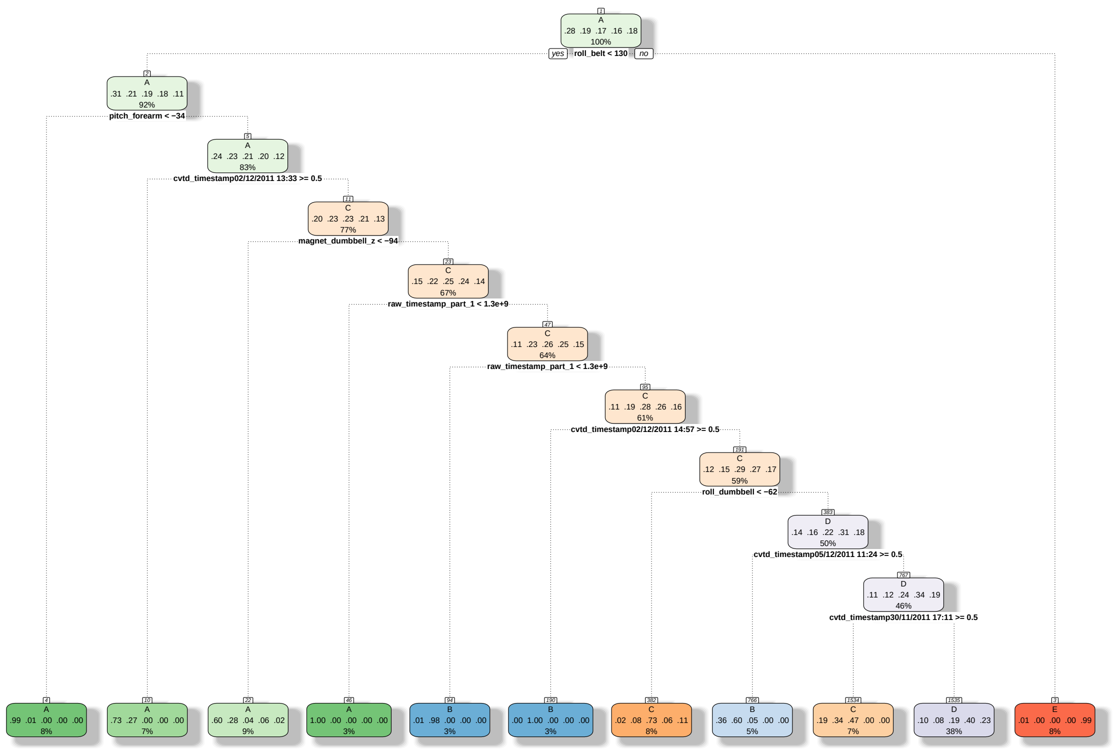
```r
inTrain <- createDataPartition(y=trainingNoNA$classe, p=0.6, list=FALSE)
pmlTraining <- trainingNoNA[inTrain, ]
pmlTesting <- trainingNoNA[-inTrain, ]
dim(pmlTraining); dim(pmlTesting)
```

```
## [1] 11776    57
```

```
## [1] 7846   57
```

The first model we want to examine is a Tree as this is a simple and powerful method that allows for easy interpreation.

```r
modeltree <- train(classe~.,data=pmlTraining, method = "rpart")
fancyRpartPlot(modeltree$finalModel)
```



Rattle 2015−Nov−18 10:16:11 kyoung

Then we want to look at how well it predicts the testing data we created

```r
predicttree <- predict(modeltree, pmlTesting)
confusionMatrix(predicttree, pmlTesting$classe)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1686  336   42   46   19
##          B  143  658   13    0    0
##          C  127  255  714   32   92
##          D  268  269  599 1208  694
##          E    8    0    0    0  637
##
## Overall Statistics
##
##                Accuracy : 0.6249
##                  95% CI : (0.6141, 0.6356)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.5294
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.7554  0.43347   0.5219   0.9393  0.44175
## Specificity            0.9211  0.97535   0.9219   0.7210  0.99875
## Pos Pred Value         0.7919  0.80835   0.5852   0.3976  0.98760
## Neg Pred Value         0.9045  0.87770   0.9013   0.9838  0.88821
## Prevalence             0.2845  0.19347   0.1744   0.1639  0.18379
## Detection Rate         0.2149  0.08386   0.0910   0.1540  0.08119
## Detection Prevalence   0.2713  0.10375   0.1555   0.3872  0.08221
## Balanced Accuracy      0.8382  0.70441   0.7219   0.8302  0.72025
```

This model is not very accurate - only 62%. We should try a different approach, so the next model we use is a random forrest model as this model tends to be more accurate than a simple tree.

```r
modelrf <- randomForest(classe~.,data=pmlTraining)
```

And now for how well it predicts

```r
predictrf<- predict(modelrf, pmlTesting)
confusionMatrix(predictrf, pmlTesting$classe)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 2230    0    0    0    0
##          B    2 1518    2    0    0
##          C    0    0 1361    0    0
##          D    0    0    5 1286    1
##          E    0    0    0    0 1441
##
## Overall Statistics
##
##                Accuracy : 0.9987
##                  95% CI : (0.9977, 0.9994)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9984
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9991   1.0000   0.9949   1.0000   0.9993
## Specificity            1.0000   0.9994   1.0000   0.9991   1.0000
## Pos Pred Value         1.0000   0.9974   1.0000   0.9954   1.0000
## Neg Pred Value         0.9996   1.0000   0.9989   1.0000   0.9998
## Prevalence             0.2845   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2842   0.1935   0.1735   0.1639   0.1837
## Detection Prevalence   0.2842   0.1940   0.1735   0.1647   0.1837
## Balanced Accuracy      0.9996   0.9997   0.9974   0.9995   0.9997
```

This is much better, with an accuracy of 99%. This is therefore the model we will use to predict the provided test data for the assignment.

We need the test data to have the same columns as the training data, so next we make sure the data sets have the same variables/columns

```r
pml.testing <- read.csv("~/Desktop/courseraR/pml-testing.csv")
columnsused <- colnames(pmlTraining[,-57])
ClassTesting <- pml.testing[columnsused]
dim(ClassTesting)
```

```
## [1] 20 56
```

Now we predict the test data (note that I gave up getting random forrest to predict. I spent hours searching but could never get past the error "Type of predictors in the new data do not match that of the training data" so the results below are from the poorer tree model)

```r
predictTest <- predict(modeltree, ClassTesting)
predictTest
```

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

A final note on error: The out of sample error rate, or generalization error, is the error set you get on a new data set. This will usually be higher than the in sample error rate due to some overfitting. In the tree model the out of sample error was 1-0.62 = 0.38, not very good. In the random forrest model the out of sample error was 1-0.99 = 0.01, a very good error rate and thus one reason we selected this model as the final model.