Loading Data and Libraries

Loading all the libraries and the data

```
library(lattice)
library(ggplot2)
library(caret)
library(kernlab)
library(rattle)
library(corrplot)
set.seed(1234)
traincsv <- read.csv("./data/pml-training.csv")
testcsv <- read.csv("./data/pml-testing.csv")

dim(traincsv)
## [1] 19622   160
dim(testcsv)
## [1]  20 160
```

We see that there are 160 variables and 19622 observations in the training set, while 20 for the test set.

Cleaning the Data

Removing unnecessary variables. Starting with N/A variables.

```
traincsv <- traincsv[,colMeans(is.na(traincsv)) < .9] #removing mostly na columns
traincsv <- traincsv[,-c(1:7)] #removing metadata which is irrelevant to the outcome
```

Removing near zero variance variables.

```
nvz <- nearZeroVar(traincsv)
traincsv <- traincsv[,-nvz]
dim(traincsv)
## [1] 19622    53
```

Now that we have finished removing the unnecessary variables, we can now split the training set into a **validation** and sub **training** set. The testing set "testcsv" will be left alone, and used for the final quiz test cases.

```
inTrain <- createDataPartition(y=traincsv$classe, p=0.7, list=F)
```

```
train <- traincsv[inTrain,]

valid <- traincsv[-inTrain,]
```

Creating and Testing the Models

Here we will test a few popular models including: **Decision Trees**, **Random Forest**, **Gradient Boosted Trees**, and **SVM**. This is probably more than we will need to test, but just out of curiosity and good practice we will run them for comparison.

Set up control for training to use 3-fold cross validation.

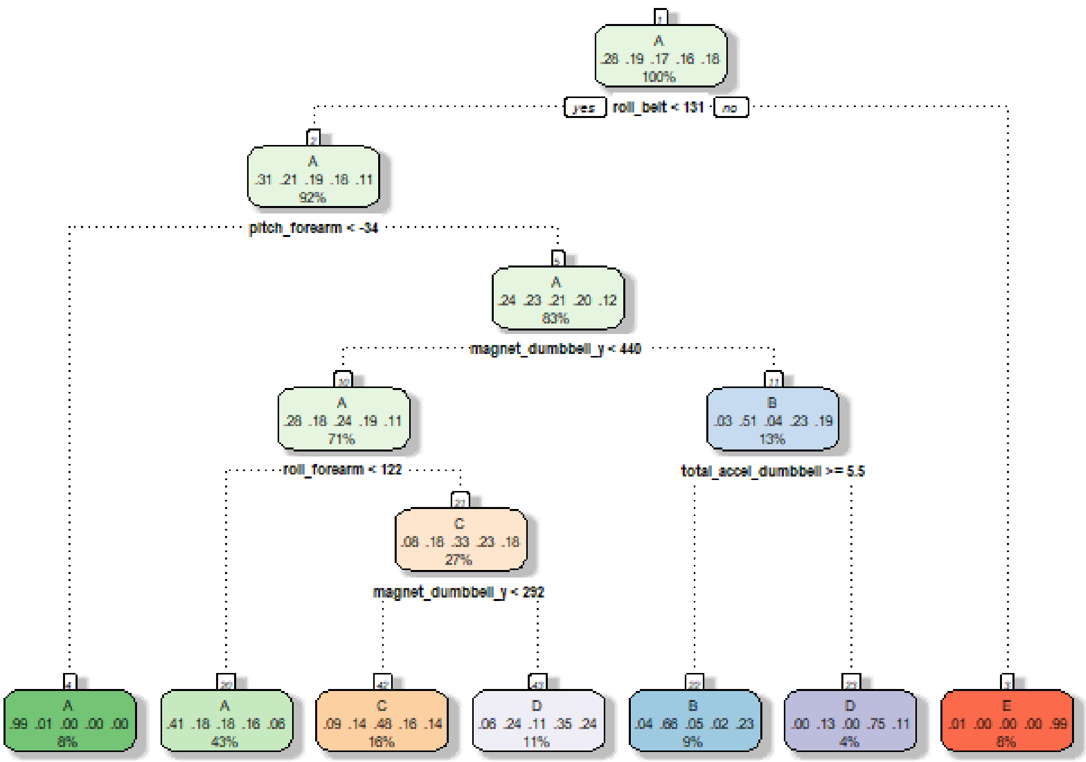
```
control <- trainControl(method="cv", number=3, verboseIter=F)
```

Decision Tree

Model:

```
mod_trees <- train(classe~., data=train, method="rpart", trControl = contro
l, tuneLength = 5)

fancyRpartPlot(mod_trees$finalModel)
```



Prediction:

```
pred_trees <- predict(mod_trees, valid)

cmtrees <- confusionMatrix(pred_trees, factor(valid$classe))
```

```
cmtrees
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1519  473  484  451  156
##          B   28  355   45   10  130
##          C   83  117  423  131  131
##          D   40  194   74  372  176
##          E    4    0    0    0  489
##
## Overall Statistics
##
##                Accuracy : 0.5366
##                  95% CI : (0.5238, 0.5494)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.3957
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9074  0.31168  0.41228  0.38589  0.45194
## Specificity            0.6286  0.95512  0.90492  0.90165  0.99917
## Pos Pred Value         0.4927  0.62500  0.47797  0.43458  0.99189
## Neg Pred Value         0.9447  0.85255  0.87940  0.88228  0.89002
## Prevalence             0.2845  0.19354  0.17434  0.16381  0.18386
## Detection Rate         0.2581  0.06032  0.07188  0.06321  0.08309
## Detection Prevalence   0.5239  0.09652  0.15038  0.14545  0.08377
## Balanced Accuracy      0.7680  0.63340  0.65860  0.64377  0.72555
```

Random Forest

```
mod_rf <- train(classe~., data=train, method="rf", trControl = control, tun
eLength = 5)
```

```r
pred_rf <- predict(mod_rf, valid)
cmrf <- confusionMatrix(pred_rf, factor(valid$classe))
cmrf
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1673    4    0    0    0
##          B    1 1132    8    0    0
##          C    0    3 1016    5    1
##          D    0    0    2  958    0
##          E    0    0    0    1 1081
##
## Overall Statistics
##
##                Accuracy : 0.9958
##                  95% CI : (0.9937, 0.9972)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9946
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9994   0.9939   0.9903   0.9938   0.9991
## Specificity            0.9991   0.9981   0.9981   0.9996   0.9998
## Pos Pred Value         0.9976   0.9921   0.9912   0.9979   0.9991
## Neg Pred Value         0.9998   0.9985   0.9979   0.9988   0.9998
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2843   0.1924   0.1726   0.1628   0.1837
## Detection Prevalence   0.2850   0.1939   0.1742   0.1631   0.1839
## Balanced Accuracy      0.9992   0.9960   0.9942   0.9967   0.9994
```

Gradient Boosted Trees

```
mod_gbm <- train(classe~., data=train, method="gbm", trControl = control, t
uneLength = 5, verbose = F)


pred_gbm <- predict(mod_gbm, valid)

cmgbm <- confusionMatrix(pred_gbm, factor(valid$classe))

cmgbm
```

```
## Confusion Matrix and Statistics
##
##             Reference
## Prediction    A    B    C    D    E
##          A 1671    5    0    0    0
##          B    1 1128   15    0    0
##          C    2    6 1007    8    4
##          D    0    0    4  953    1
##          E    0    0    0    3 1077
##
## Overall Statistics
##
##                Accuracy : 0.9917
##                  95% CI : (0.989, 0.9938)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9895
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9982   0.9903   0.9815   0.9886   0.9954
## Specificity            0.9988   0.9966   0.9959   0.9990   0.9994
## Pos Pred Value         0.9970   0.9860   0.9805   0.9948   0.9972
## Neg Pred Value         0.9993   0.9977   0.9961   0.9978   0.9990
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2839   0.1917   0.1711   0.1619   0.1830
```

```
## Detection Prevalence   0.2848   0.1944   0.1745   0.1628   0.1835
## Balanced Accuracy      0.9985   0.9935   0.9887   0.9938   0.9974
```

Support Vector Machine

```
mod_svm <- train(classe~., data=train, method="svmLinear", trControl = cont
rol, tuneLength = 5, verbose = F)


pred_svm <- predict(mod_svm, valid)
cmsvm <- confusionMatrix(pred_svm, factor(valid$classe))
cmsvm
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1537  154   79   69   50
##          B   29  806   90   46  152
##          C   40   81  797  114   69
##          D   61   22   32  697   50
##          E    7   76   28   38  761
##
## Overall Statistics
##
##                Accuracy : 0.7813
##                  95% CI : (0.7705, 0.7918)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.722
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9182   0.7076   0.7768   0.7230   0.7033
## Specificity            0.9164   0.9332   0.9374   0.9665   0.9690
## Pos Pred Value         0.8137   0.7177   0.7239   0.8086   0.8363
```

```
## Neg Pred Value         0.9657   0.9301   0.9521   0.9468   0.9355
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2612   0.1370   0.1354   0.1184   0.1293
## Detection Prevalence   0.3210   0.1908   0.1871   0.1465   0.1546
## Balanced Accuracy      0.9173   0.8204   0.8571   0.8447   0.8362
```

Results (Accuracy & Out of Sample Error)

```
##      accuracy oos_error
## Tree    0.537     0.463
## RF      0.996     0.004
## GBM     0.992     0.008
## SVM     0.781     0.219
```

The best model is the Random Forest model, with 0.9957519 accuracy and 0.0042481 out of sample error rate. We find that to be a sufficient enough model to use for our test sets.

Predictions on Test Set

Running our test set to predict the classe (5 levels) outcome for 20 cases with the **Random Forest** model.

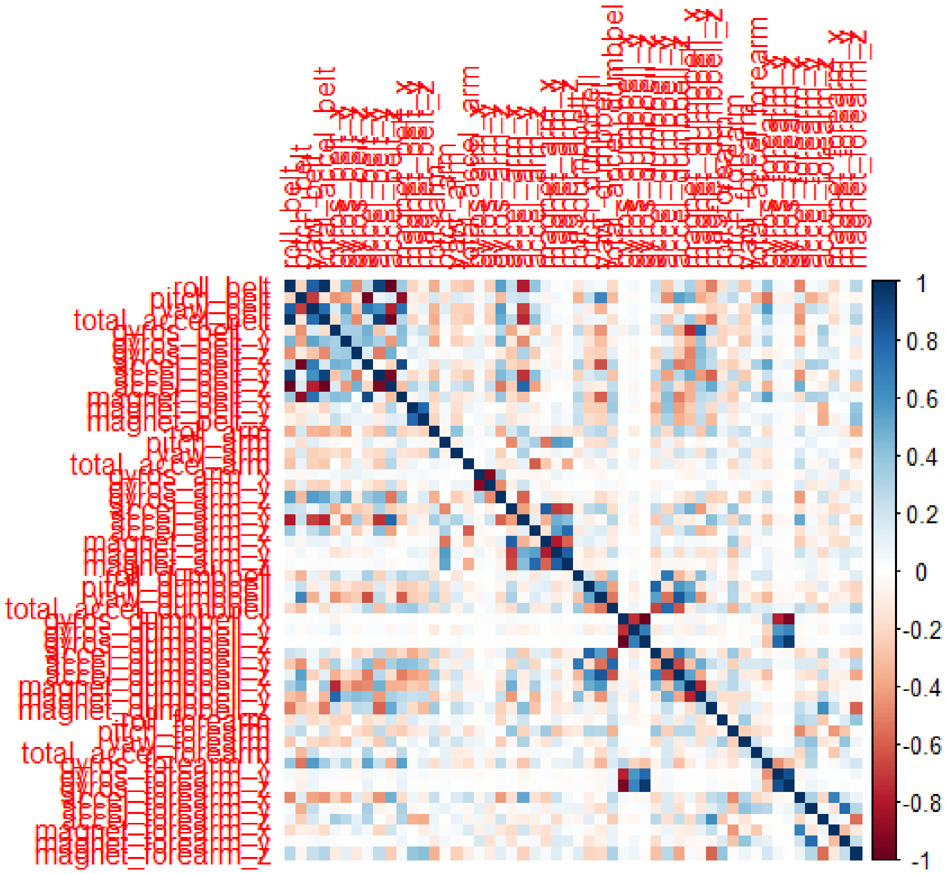
```
pred <- predict(mod_rf, testcsv)
print(pred)
##  [1] B A B A A E D B A A B C B A E E A B B B
## Levels: A B C D E
```

Appendix

Github Repo: [Github]()

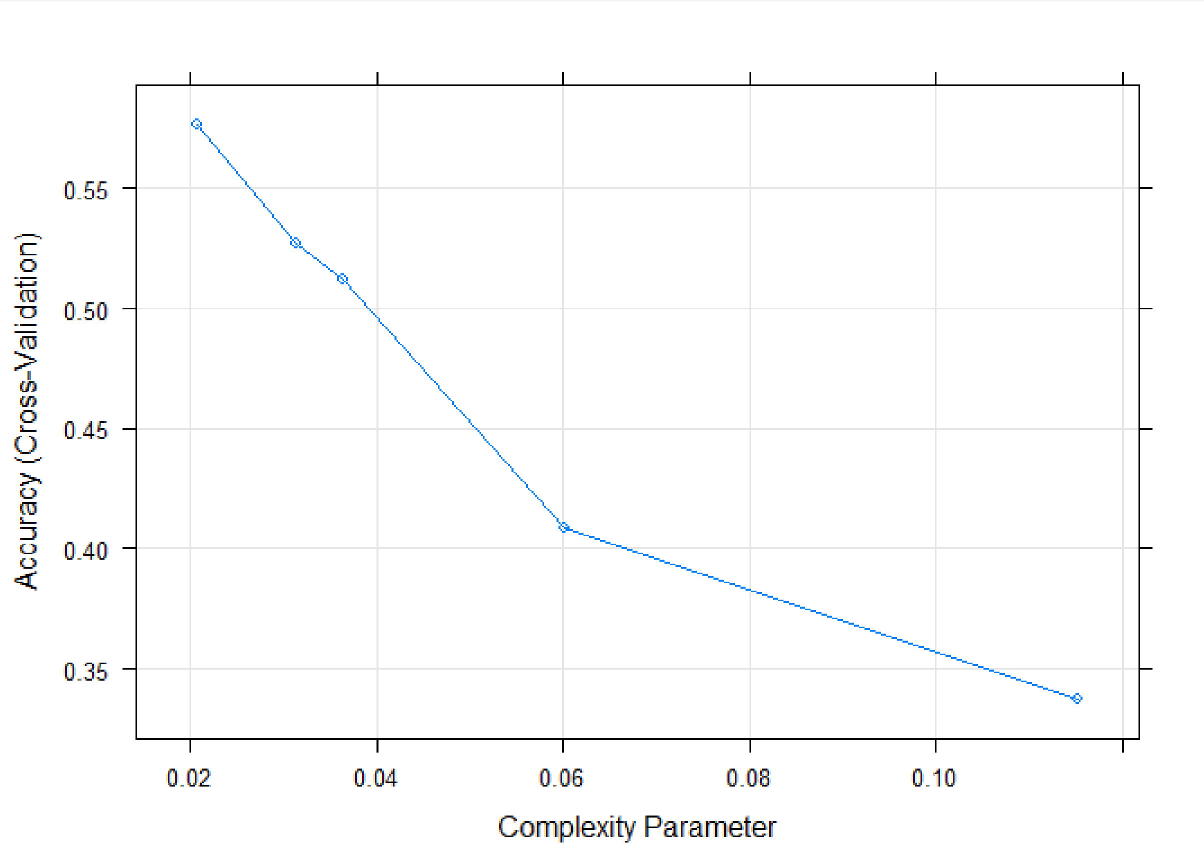
correlation matrix of variables in training set

```
corrPlot <- cor(train[, -length(names(train))])
corrplot(corrPlot, method="color")
```

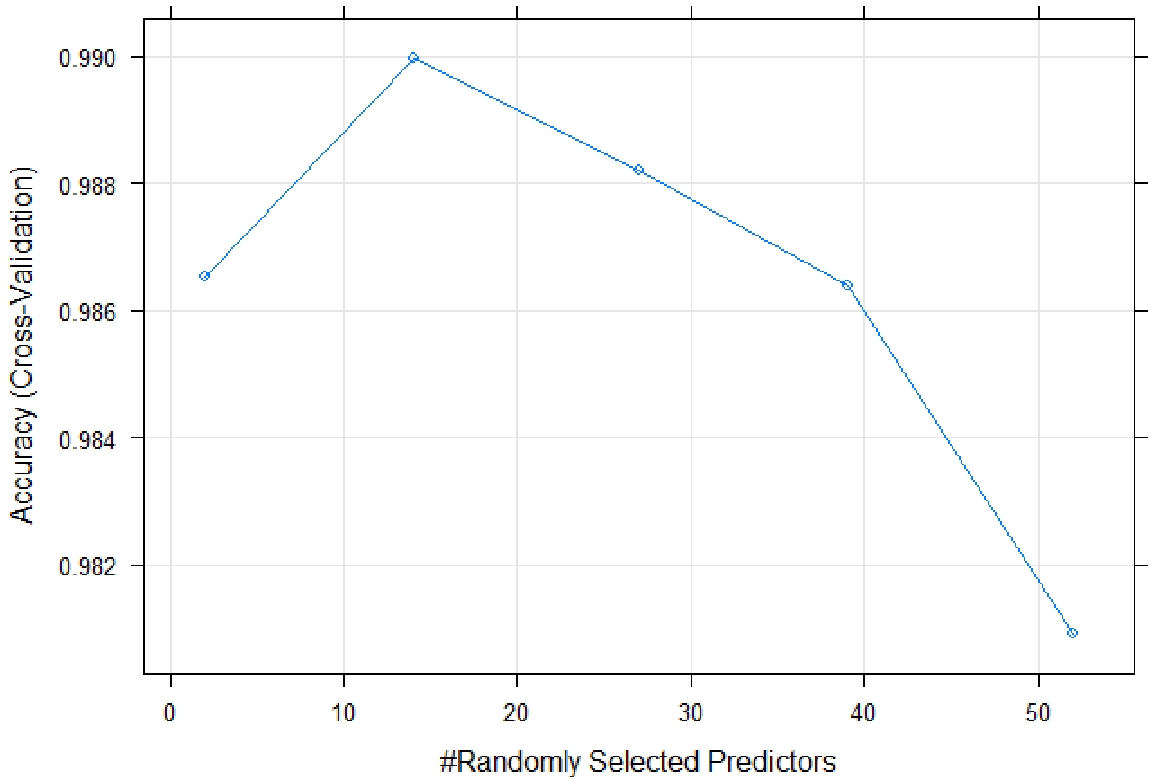


Plotting the models

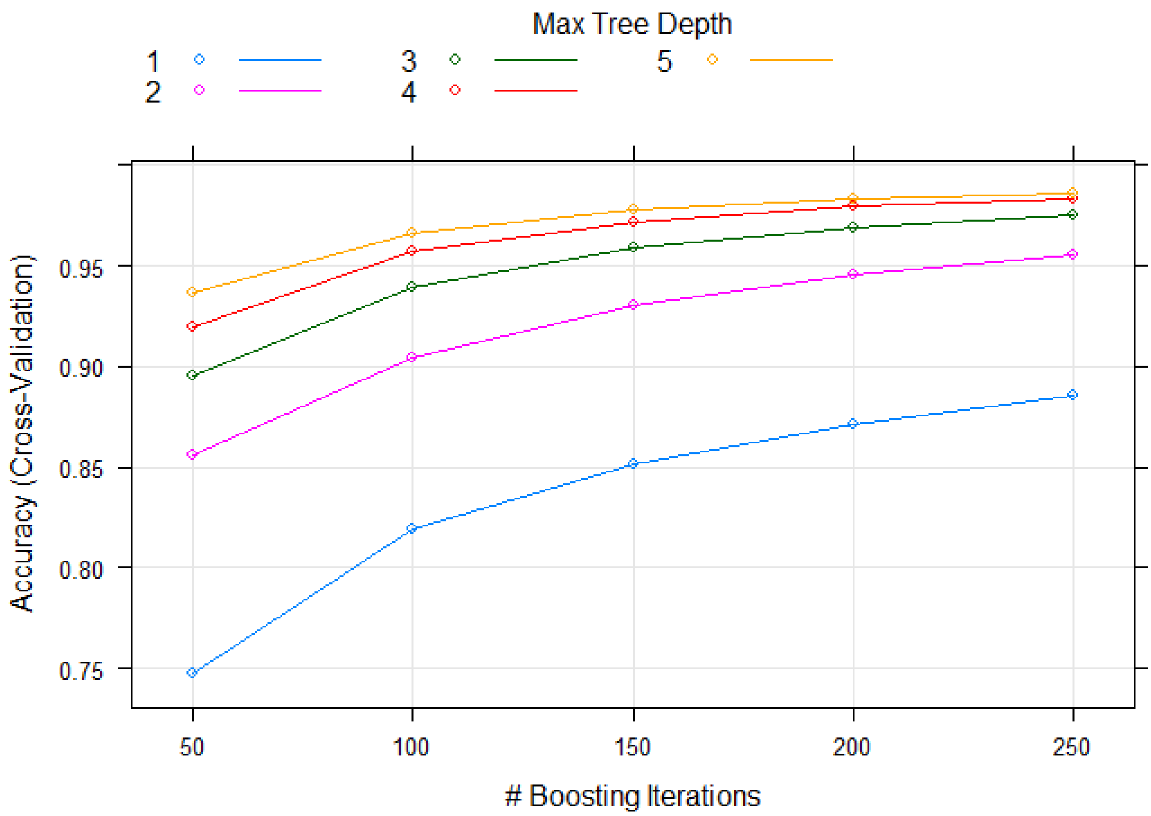
```
plot(mod_trees)
```




```
plot(mod_rf)
```


0.990
0.988
0.986
0.984
0.982
Accuracy (Cross-Validation)
0
10
20
30
40
50
#Randomly Selected Predictors

```
plot(mod_gbm)
```


Max Tree Depth
1
2
3
4
5
0.95
0.90
0.85
0.80
0.75
Accuracy (Cross-Validation)
50
100
150
200
250
Boosting Iterations