Coursera - Practical Machine Learning Project - Ramesh NBN

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1 Coursera - Practical Machine Learning Project

1.0.1 by Ramesh NBN

1.1 Introduction and 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).

I would like to try different models such as **"Classification Trees", "Random Forest", "Gradient Boosting"** and evaluate the best model to find the predicted classification values on the test data.

1.2 Install and load required packages

[1]:
```
#install.packages("e1071")
#install.packages("rattle")
#install.packages("gbm")
```

[2]:
```
library(caret)
library(rattle)
```

```
Loading required package: lattice
Loading required package: ggplot2
Rattle: A free graphical interface for data science with R.
Version 5.2.0 Copyright (c) 2006-2018 Togaware Pty Ltd.
Type 'rattle()' to shake, rattle, and roll your data.
```

2 load the downloaded data from

https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv and https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv

[3]:
```
trainingData = read.csv("pml-training.csv",na.strings=c("NA",""))

testingData = read.csv("pml-testing.csv",na.strings=c("NA",""))
```

A quick look of the training data

[4]:
```
head(trainingData)
```

A data.frame: 6 × 160

X <int>	user_name <fct>	raw_timestamp_part_1 <int>	raw_timestamp_part_2 <int>	cvtd_timesta <fct>
1	carlitos	1323084231	788290	05/12/2011 1
2	carlitos	1323084231	808298	05/12/2011 1
3	carlitos	1323084231	820366	05/12/2011 1
4	carlitos	1323084232	120339	05/12/2011 1
5	carlitos	1323084232	196328	05/12/2011 1
6	carlitos	1323084232	304277	05/12/2011 1

Summary of the data is too large

[5]:
```
#summary(trainingData)
```

[6]:
```
#names(trainingData)
```

2.1 Data cleansing

To find the columns having NA

[7]:
```
#colSums(is.na(trainingData)==0)
```

Remove the columns which contain NA

[8]:
```
training <- trainingData[, colSums(is.na(trainingData)) == 0]
testing <- testingData[, colSums(is.na(testingData)) == 0]
```

Remove first 7 columns as they do not participate in the classification of the data

[9]:
```
trainData <- training[, -c(1:7)]
testData <- testing[, -c(1:7)]
```

2.2 Split the train data into train and validation sets

[10]:
```
set.seed(3328)

#Divide the train data into 70,30 train and validation sets
inTrain <- createDataPartition(trainData$classe, p = 0.7, list = FALSE)

train <- trainData[inTrain, ]
```

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

2.3 Build the training control set using 3 fold cross validation sets

[11]:
```
control <- trainControl(method = "cv", number = 3)
```

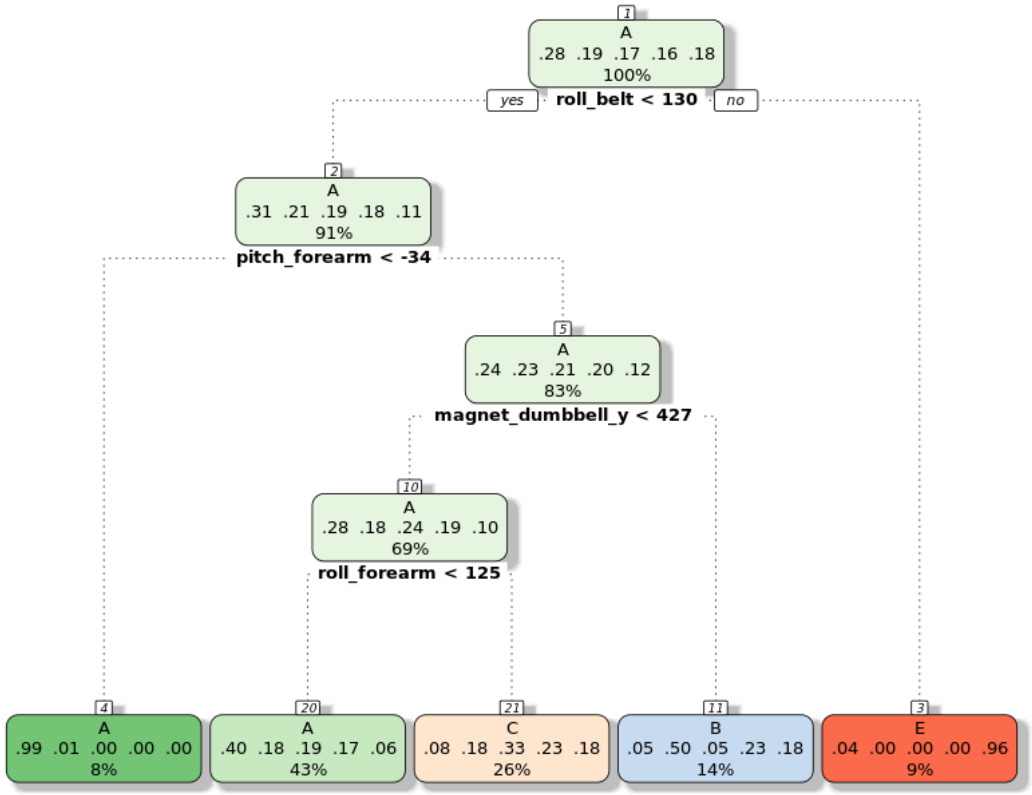
2.4 Train using Classification Tree model with recursive partitioning method

Build the model and have a quick look of the model

[12]:
```
fit_rpart <- train(classe ~ ., data = train, method = "rpart", trControl =␣
 ↪control)

print(fit_rpart, digits = 4)
```

```
CART

13737 samples
   52 predictor
    5 classes: 'A', 'B', 'C', 'D', 'E'

No pre-processing
Resampling: Cross-Validated (3 fold)
Summary of sample sizes: 9158, 9158, 9158
Resampling results across tuning parameters:

  cp       Accuracy  Kappa
  0.03357  0.5016    0.34952
  0.05954  0.4074    0.19498
  0.11616  0.3118    0.04198

Accuracy was used to select the optimal model using the largest value.
The final value used for the model was cp = 0.03357.
```

[13]:
```
fancyRpartPlot(fit_rpart$finalModel)
```



Rattle 2019-Nov-20 10:57:59 jupyterlab

Predict and validate using the validation set

[14]:
```
predict_rpart <- predict(fit_rpart, valid)

cfm_rpart <- confusionMatrix(valid$classe, predict_rpart)
```

[15]:
```
cfm_rpart$table
```

```
          Reference
Prediction    A    B    C    D    E
         A 1500   37  111    0   26
         B  460  418  261    0    0
         C  460   41  525    0    0
```

```
D  418  191  355    0    0
E  137  151  285    0  509
```

[17]:
```
#Accuracy of the prediction
cfm_rpart$overall[1]
```

Accuracy: 0.50161427357689

The accuracy of this model is not good. Hence let's try our next model using Random Forest

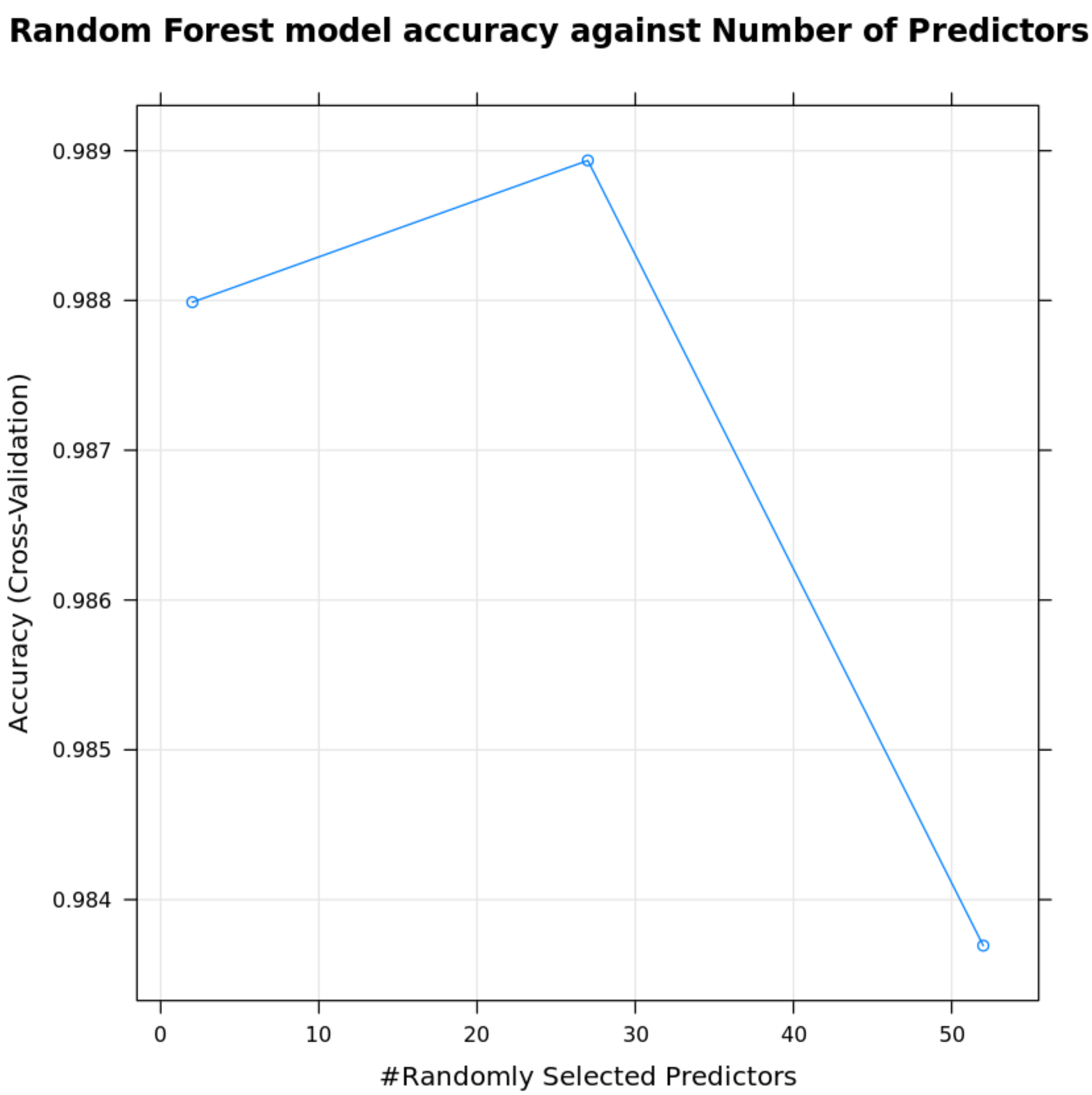
2.5 Train using Random Forest classification model

Build the model and have a quick look

[18]:
```
fit_rf <- train(classe ~ ., data = train, method = "rf", trControl = control)

print(fit_rf)
```

```
Random Forest

13737 samples
   52 predictor
    5 classes: 'A', 'B', 'C', 'D', 'E'

No pre-processing
Resampling: Cross-Validated (3 fold)
Summary of sample sizes: 9157, 9160, 9157
Resampling results across tuning parameters:

  mtry  Accuracy   Kappa
   2    0.9879886  0.9848048
  27    0.9889347  0.9860021
  52    0.9836928  0.9793724

Accuracy was used to select the optimal model using the largest value.
The final value used for the model was mtry = 27.
```

[19]:
```
plot(fit_rf, main="Random Forest model accuracy against Number of Predictors")
```



[20]:
```
predict_rf <- predict(fit_rf,valid)
```

[21]:
```
cfm_rf <- confusionMatrix(valid$classe, predict_rf)
```

[22]:
```
cfm_rf$table
```

```
          Reference
Prediction    A    B    C    D    E
         A 1671    2    0    0    1
         B    9 1127    3    0    0
         C    0    2 1023    1    0
         D    0    0    8  956    0
         E    0    0    1    2 1079
```

[23]:
```
cfm_rf$overall[1]
```

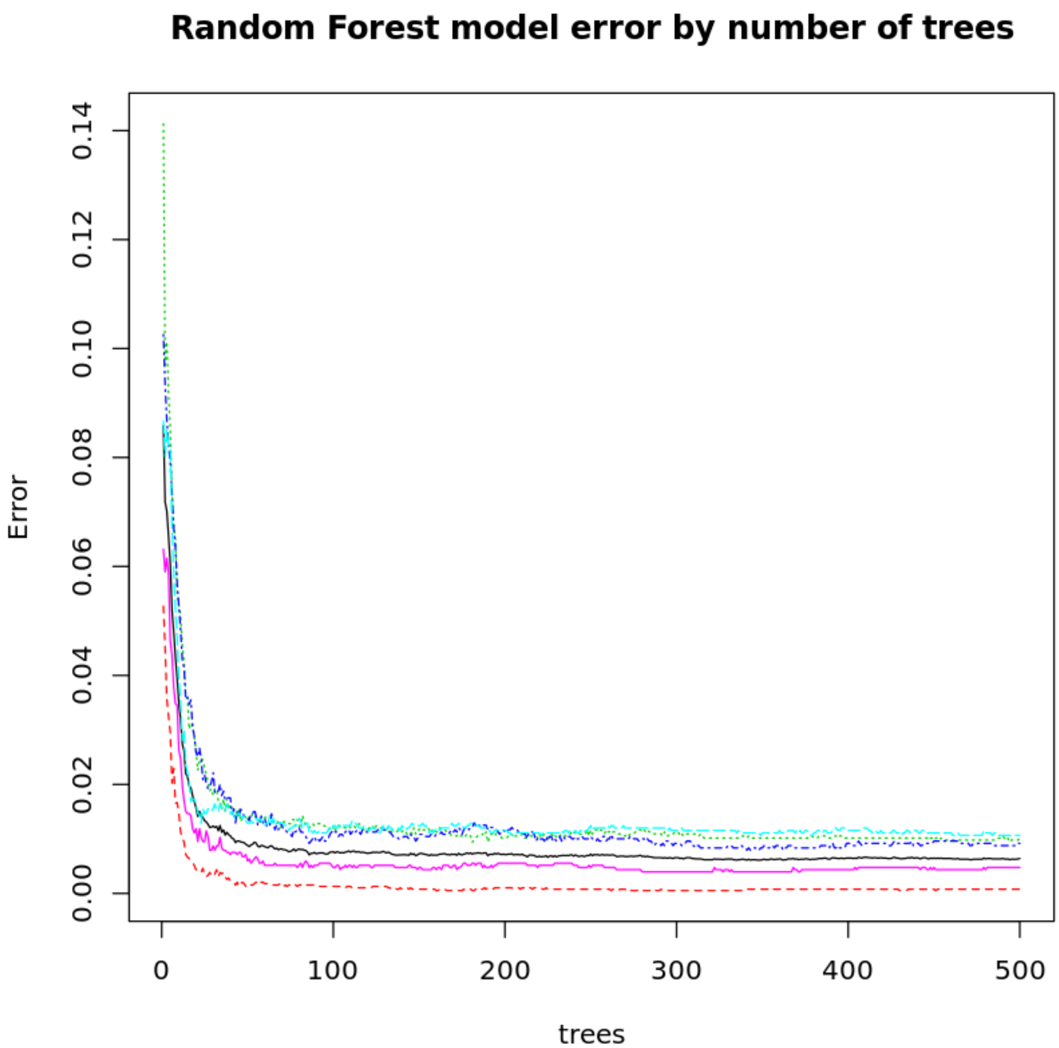
Accuracy: 0.995072217502124

The accuracy of this model is very good and giving the confidence level above 99 using 3 fold cross validation sets. Let's have very close look of the model. Though this model seems to be much promising, we will try Gradient Boosting model and evaluate that too.

[24]:
```
names(fit_rf$finalModel)
```

1. 'call' 2. 'type' 3. 'predicted' 4. 'err.rate' 5. 'confusion' 6. 'votes' 7. 'oob.times' 8. 'classes' 9. 'importance' 10. 'importanceSD' 11. 'localImportance' 12. 'proximity' 13. 'ntree' 14. 'mtry' 15. 'forest' 16. 'y' 17. 'test' 18. 'inbag' 19. 'xNames' 20. 'problemType' 21. 'tuneValue' 22. 'obsLevels' 23. 'param'

[25]:
```
plot(fit_rf$finalModel,main="Random Forest model error by number of trees")
```



[26]:

```
#Important variables used in building the model
varImp(fit_rf)
```

```
rf variable importance

  only 20 most important variables shown (out of 52)

                     Overall
roll_belt             100.00
pitch_forearm          61.89
yaw_belt               55.80
magnet_dumbbell_z      46.11
pitch_belt             45.27
```

```
magnet_dumbbell_y      41.96
roll_forearm           38.65
accel_dumbbell_y       20.94
roll_dumbbell          19.11
magnet_dumbbell_x      18.49
accel_forearm_x        16.64
magnet_belt_z          15.01
total_accel_dumbbell   14.99
accel_belt_z           14.42
accel_dumbbell_z       14.17
magnet_belt_y          13.69
magnet_forearm_z       13.35
yaw_arm                11.25
gyros_belt_z           11.23
magnet_belt_x          10.21
```

2.6 Train the model using Gradient Boosting method

[27]:
```r
fit_gbm <- train(classe ~ ., data = train, method = "gbm", trControl = control)

print(fit_gbm)
```

```
Iter   TrainDeviance   ValidDeviance   StepSize   Improve
     1        1.6094             -nan     0.1000    0.1312
     2        1.5208             -nan     0.1000    0.0882
     3        1.4619             -nan     0.1000    0.0655
     4        1.4170             -nan     0.1000    0.0554
     5        1.3806             -nan     0.1000    0.0442
     6        1.3517             -nan     0.1000    0.0434
     7        1.3235             -nan     0.1000    0.0426
     8        1.2970             -nan     0.1000    0.0335
     9        1.2758             -nan     0.1000    0.0303
    10        1.2559             -nan     0.1000    0.0236
    20        1.1012             -nan     0.1000    0.0177
    40        0.9302             -nan     0.1000    0.0107
    60        0.8226             -nan     0.1000    0.0065
    80        0.7424             -nan     0.1000    0.0041
   100        0.6797             -nan     0.1000    0.0023
   120        0.6278             -nan     0.1000    0.0022
   140        0.5870             -nan     0.1000    0.0019
   150        0.5666             -nan     0.1000    0.0013

Iter   TrainDeviance   ValidDeviance   StepSize   Improve
     1        1.6094             -nan     0.1000    0.1899
     2        1.4865             -nan     0.1000    0.1266
     3        1.4040             -nan     0.1000    0.1051
     4        1.3355             -nan     0.1000    0.0855
```

5	1.2810	-nan	0.1000	0.0719
6	1.2349	-nan	0.1000	0.0668
7	1.1928	-nan	0.1000	0.0612
8	1.1543	-nan	0.1000	0.0426
9	1.1248	-nan	0.1000	0.0445
10	1.0962	-nan	0.1000	0.0447
20	0.8945	-nan	0.1000	0.0225
40	0.6844	-nan	0.1000	0.0102
60	0.5547	-nan	0.1000	0.0048
80	0.4634	-nan	0.1000	0.0053
100	0.3993	-nan	0.1000	0.0025
120	0.3466	-nan	0.1000	0.0038
140	0.3027	-nan	0.1000	0.0014
150	0.2858	-nan	0.1000	0.0024

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	1.6094	-nan	0.1000	0.2280
2	1.4631	-nan	0.1000	0.1651
3	1.3585	-nan	0.1000	0.1301
4	1.2751	-nan	0.1000	0.1005
5	1.2113	-nan	0.1000	0.0899
6	1.1547	-nan	0.1000	0.0757
7	1.1062	-nan	0.1000	0.0665
8	1.0628	-nan	0.1000	0.0681
9	1.0191	-nan	0.1000	0.0553
10	0.9838	-nan	0.1000	0.0474
20	0.7593	-nan	0.1000	0.0223
40	0.5305	-nan	0.1000	0.0131
60	0.4036	-nan	0.1000	0.0048
80	0.3195	-nan	0.1000	0.0035
100	0.2607	-nan	0.1000	0.0018
120	0.2199	-nan	0.1000	0.0023
140	0.1875	-nan	0.1000	0.0016
150	0.1718	-nan	0.1000	0.0019

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	1.6094	-nan	0.1000	0.1301
2	1.5227	-nan	0.1000	0.0895
3	1.4626	-nan	0.1000	0.0668
4	1.4177	-nan	0.1000	0.0550
5	1.3810	-nan	0.1000	0.0505
6	1.3480	-nan	0.1000	0.0421
7	1.3203	-nan	0.1000	0.0335
8	1.2973	-nan	0.1000	0.0373
9	1.2742	-nan	0.1000	0.0349
10	1.2511	-nan	0.1000	0.0268
20	1.0989	-nan	0.1000	0.0197
40	0.9276	-nan	0.1000	0.0104

```
    60        0.8167             -nan     0.1000    0.0045
    80        0.7400             -nan     0.1000    0.0053
   100        0.6772             -nan     0.1000    0.0039
   120        0.6264             -nan     0.1000    0.0047
   140        0.5807             -nan     0.1000    0.0023
   150        0.5611             -nan     0.1000    0.0026

Iter   TrainDeviance   ValidDeviance   StepSize   Improve
     1        1.6094             -nan     0.1000    0.1830
     2        1.4884             -nan     0.1000    0.1332
     3        1.4033             -nan     0.1000    0.1002
     4        1.3374             -nan     0.1000    0.0910
     5        1.2795             -nan     0.1000    0.0653
     6        1.2358             -nan     0.1000    0.0583
     7        1.1981             -nan     0.1000    0.0666
     8        1.1568             -nan     0.1000    0.0487
     9        1.1254             -nan     0.1000    0.0452
    10        1.0958             -nan     0.1000    0.0483
    20        0.8942             -nan     0.1000    0.0180
    40        0.6835             -nan     0.1000    0.0105
    60        0.5564             -nan     0.1000    0.0079
    80        0.4667             -nan     0.1000    0.0055
   100        0.3996             -nan     0.1000    0.0041
   120        0.3464             -nan     0.1000    0.0034
   140        0.3037             -nan     0.1000    0.0024
   150        0.2837             -nan     0.1000    0.0012

Iter   TrainDeviance   ValidDeviance   StepSize   Improve
     1        1.6094             -nan     0.1000    0.2325
     2        1.4613             -nan     0.1000    0.1654
     3        1.3556             -nan     0.1000    0.1270
     4        1.2742             -nan     0.1000    0.1040
     5        1.2084             -nan     0.1000    0.0899
     6        1.1507             -nan     0.1000    0.0732
     7        1.1047             -nan     0.1000    0.0575
     8        1.0666             -nan     0.1000    0.0606
     9        1.0274             -nan     0.1000    0.0636
    10        0.9876             -nan     0.1000    0.0526
    20        0.7503             -nan     0.1000    0.0218
    40        0.5229             -nan     0.1000    0.0100
    60        0.4041             -nan     0.1000    0.0065
    80        0.3215             -nan     0.1000    0.0056
   100        0.2628             -nan     0.1000    0.0049
   120        0.2199             -nan     0.1000    0.0012
   140        0.1882             -nan     0.1000    0.0024
   150        0.1743             -nan     0.1000    0.0013

Iter   TrainDeviance   ValidDeviance   StepSize   Improve
```

1	1.6094	-nan	0.1000	0.1225
2	1.5248	-nan	0.1000	0.0852
3	1.4673	-nan	0.1000	0.0631
4	1.4248	-nan	0.1000	0.0526
5	1.3888	-nan	0.1000	0.0499
6	1.3572	-nan	0.1000	0.0391
7	1.3319	-nan	0.1000	0.0367
8	1.3081	-nan	0.1000	0.0384
9	1.2835	-nan	0.1000	0.0301
10	1.2623	-nan	0.1000	0.0278
20	1.1070	-nan	0.1000	0.0156
40	0.9335	-nan	0.1000	0.0075
60	0.8268	-nan	0.1000	0.0043
80	0.7482	-nan	0.1000	0.0041
100	0.6836	-nan	0.1000	0.0018
120	0.6318	-nan	0.1000	0.0031
140	0.5862	-nan	0.1000	0.0035
150	0.5663	-nan	0.1000	0.0013

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	1.6094	-nan	0.1000	0.1850
2	1.4879	-nan	0.1000	0.1231
3	1.4062	-nan	0.1000	0.1007
4	1.3407	-nan	0.1000	0.0812
5	1.2890	-nan	0.1000	0.0632
6	1.2473	-nan	0.1000	0.0568
7	1.2107	-nan	0.1000	0.0605
8	1.1730	-nan	0.1000	0.0468
9	1.1430	-nan	0.1000	0.0499
10	1.1116	-nan	0.1000	0.0389
20	0.9034	-nan	0.1000	0.0197
40	0.6855	-nan	0.1000	0.0110
60	0.5573	-nan	0.1000	0.0066
80	0.4715	-nan	0.1000	0.0045
100	0.4055	-nan	0.1000	0.0045
120	0.3467	-nan	0.1000	0.0019
140	0.3055	-nan	0.1000	0.0019
150	0.2869	-nan	0.1000	0.0015

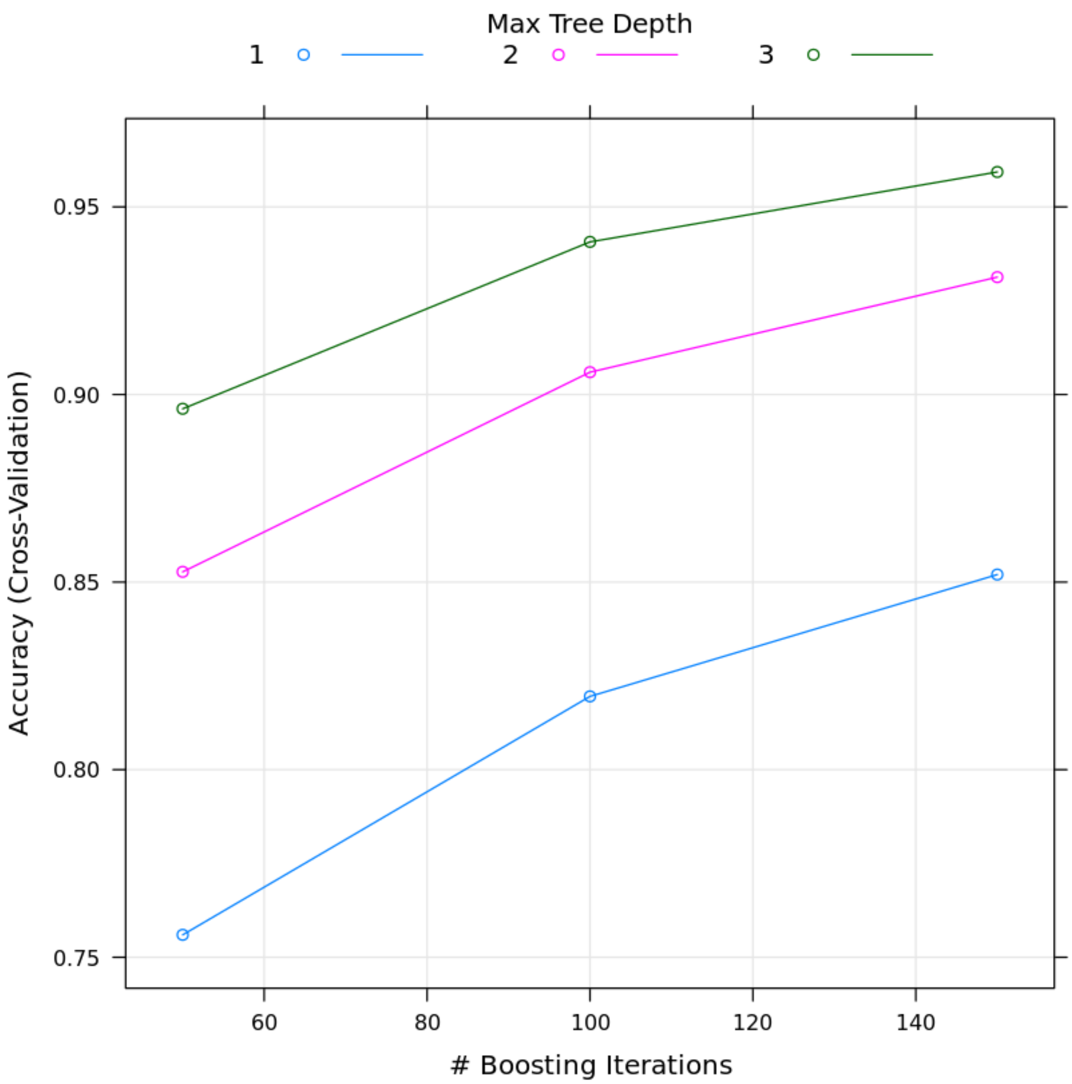
Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	1.6094	-nan	0.1000	0.2330
2	1.4622	-nan	0.1000	0.1646
3	1.3573	-nan	0.1000	0.1219
4	1.2783	-nan	0.1000	0.1023
5	1.2139	-nan	0.1000	0.0817
6	1.1598	-nan	0.1000	0.0775
7	1.1095	-nan	0.1000	0.0643
8	1.0670	-nan	0.1000	0.0725

```
     9        1.0213             -nan     0.1000    0.0449
    10        0.9916             -nan     0.1000    0.0493
    20        0.7612             -nan     0.1000    0.0221
    40        0.5342             -nan     0.1000    0.0144
    60        0.4055             -nan     0.1000    0.0078
    80        0.3243             -nan     0.1000    0.0063
   100        0.2644             -nan     0.1000    0.0039
   120        0.2210             -nan     0.1000    0.0013
   140        0.1860             -nan     0.1000    0.0008
   150        0.1716             -nan     0.1000    0.0017

Iter   TrainDeviance   ValidDeviance   StepSize   Improve
     1        1.6094             -nan     0.1000    0.2296
     2        1.4646             -nan     0.1000    0.1653
     3        1.3604             -nan     0.1000    0.1258
     4        1.2813             -nan     0.1000    0.1020
     5        1.2154             -nan     0.1000    0.0931
     6        1.1588             -nan     0.1000    0.0834
     7        1.1062             -nan     0.1000    0.0630
     8        1.0665             -nan     0.1000    0.0550
     9        1.0315             -nan     0.1000    0.0603
    10        0.9938             -nan     0.1000    0.0488
    20        0.7673             -nan     0.1000    0.0223
    40        0.5377             -nan     0.1000    0.0107
    60        0.4059             -nan     0.1000    0.0072
    80        0.3277             -nan     0.1000    0.0057
   100        0.2698             -nan     0.1000    0.0028
   120        0.2258             -nan     0.1000    0.0020
   140        0.1934             -nan     0.1000    0.0008
   150        0.1787             -nan     0.1000    0.0014

Stochastic Gradient Boosting

13737 samples
   52 predictor
    5 classes: 'A', 'B', 'C', 'D', 'E'

No pre-processing
Resampling: Cross-Validated (3 fold)
Summary of sample sizes: 9158, 9158, 9158
Resampling results across tuning parameters:

  interaction.depth  n.trees  Accuracy   Kappa
  1                   50      0.7559875  0.6905654
  1                  100      0.8195385  0.7716429
  1                  150      0.8520055  0.8128041
  2                   50      0.8527335  0.8134300
  2                  100      0.9059474  0.8809567
```

```
  2                  150       0.9312805  0.9130328
  3                   50       0.8961928  0.8685990
  3                  100       0.9406712  0.9249153
  3                  150       0.9593070  0.9485095

Tuning parameter 'shrinkage' was held constant at a value of 0.1

Tuning parameter 'n.minobsinnode' was held constant at a value of 10
Accuracy was used to select the optimal model using the largest value.
The final values used for the model were n.trees = 150, interaction.depth =
 3, shrinkage = 0.1 and n.minobsinnode = 10.
```

[28]:

```
plot(fit_gbm)
```



[29]:
```
predict_gbm <- predict(fit_gbm,valid)
```

[30]:
```
cfm_gbm <- confusionMatrix(valid$classe, predict_gbm)
```

[31]:
```
cfm_gbm$table
```

```
          Reference
Prediction    A    B    C    D    E
         A 1648   18    5    3    0
         B   30 1081   27    0    1
         C    0   33  975   14    4
         D    0    5   32  921    6
         E    2   20   14   12 1034
```

[32]:
```
cfm_gbm$overall[1]
```

Accuracy: 0.961597281223449

The accuracy of this model with 96.15% is better than Classification Trees but not with Random forest. Hence, we conclude that Random forest is the best for this experiment.

2.7 Conclusion

From the above 3 models, Random forest is much more promising. Hence using the Random Forest model to predict the values on the test set

[33]:
```
results <- predict(fit_rf, testData)
results
```

1. B 2. A 3. B 4. A 5. A 6. E 7. D 8. B 9. A 10. A 11. B 12. C 13. B 14. A 15. E 16. E 17. A 18. B 19. B 20. B

Levels: 1. 'A' 2. 'B' 3. 'C' 4. 'D' 5. 'E'