Practical Machine Learning

Peer Assessments

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Executive Summary

This document presents the results of the Practical Machine Learning Peer Assessments in a report using a single R markdown document that can be processed by knitr and be transformed into an HTML file.

This analysis was done to predict the manner in which the subjects performed weight lifting exercises. The data is collected from accelerometers on the belt, forearm, arm, and dumbell of 6 participants. The outcome variable has five classes and the total number of predictors are 159.

Introduction

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, the 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://groupware.les.inf.puc-rio.br/har (see the section on the Weight Lifting Exercise Dataset).

Preparation

The warnings messages was keept for research reproducibility purpose

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

```
## Warning: package 'caret' was built under R version 3.3.1
```

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

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

```r
library(rpart)
```

```
## Warning: package 'rpart' was built under R version 3.3.1
```

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

```
## Warning: package 'rpart.plot' was built under R version 3.3.1
```

```
library(randomForest)
```

```
## Warning: package 'randomForest' was built under R version 3.3.1
```

```
## randomForest 4.6-12
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

```
##
## Attaching package: 'randomForest'
```

```
## The following object is masked from 'package:ggplot2':
##
##     margin
```

```
library(corrplot)
```

```
## Warning: package 'corrplot' was built under R version 3.3.1
```

```
library(rattle)
```

```
## Warning: package 'rattle' was built under R version 3.3.1
```

```
## Rattle: A free graphical interface for data mining with R.
## Version 4.1.0 Copyright (c) 2006-2015 Togaware Pty Ltd.
## Type 'rattle()' to shake, rattle, and roll your data.
```

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

Loading Data

The training data for this project are downloaded from here

The test data are downloaded from here

The data for this project come from this source

```
training <- read.csv("pml-training.csv")
testing <- read.csv("pml-testing.csv")
inTrain  <- createDataPartition(training$classe, p=0.7, list=FALSE)
TrainSet <- training[inTrain, ]
TestSet  <- training[-inTrain, ]
```

The next step is loading the dataset from the URL provided above. The training dataset is then partinioned in 2 to create a Training set (70% of the data) for the modeling process and a Test set (with the remaining 30%) for the validations. The testing dataset is not changed and will only be used for the quiz results generation

Preprocessing

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

```
## [1] 13737   106
```

```
## [1] 5885  106
```

Data Cleaning

Remove variables with missing values

```
AllNA    <- sapply(TrainSet, function(x) mean(is.na(x))) > 0.95
TrainSet <- TrainSet[, AllNA==FALSE]
TestSet  <- TestSet[, AllNA==FALSE]
dim(TrainSet)
```

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

Remove unnecessary columns

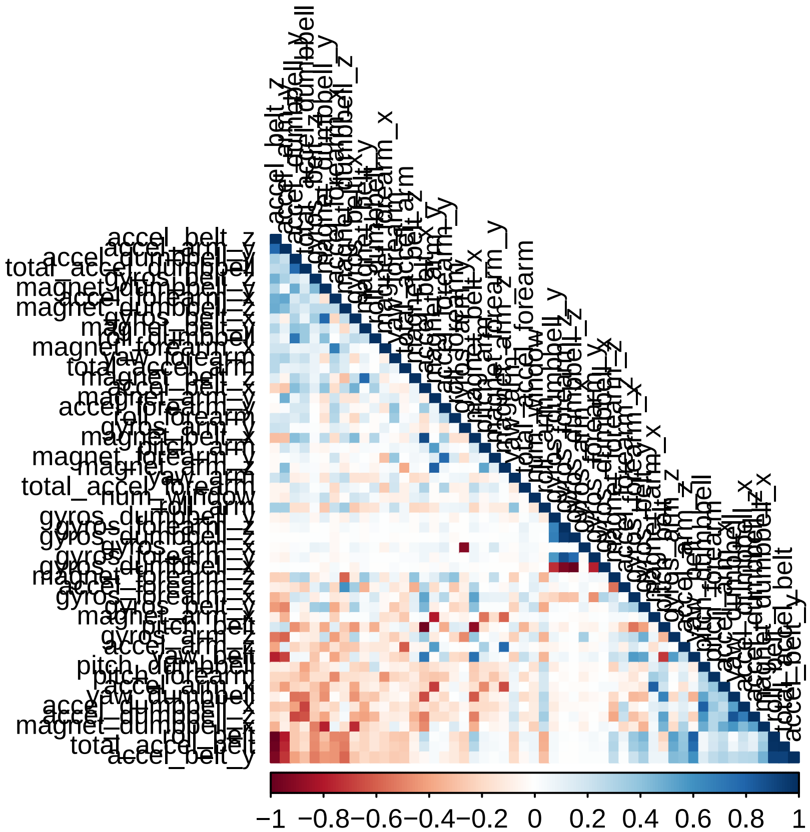
```
TrainSet <- TrainSet[, -(1:5)]
TestSet  <- TestSet[, -(1:5)]
dim(TrainSet); dim(TestSet)
```

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

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

Verifying Correlation Analysis

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



Modeling - Prediction Model Building

Since a random forest model is chosen and the data set must first be checked on possibility of columns without data.

The decision is made whereby all the columns that having less than 60% of data filled are removed.

In the new training set and validation set we just created, there are 52 predictors and 1 response. Check the correlations between the predictors and the outcome variable in the new training set. There doesn't seem to be any predictors strongly correlated with the outcome variable, so linear regression model may not be a good option. Random forest model may be more robust for this data.

Random Forest Model

Just try to fit a random forest model and check the model performance on the validation set.

```
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: 0.2%
## Confusion matrix:
##      A    B    C    D    E  class.error
## A 3904    1    0    0    1 0.0005120328
## B    5 2652    1    0    0 0.0022573363
## C    0    5 2390    1    0 0.0025041736
## D    0    0    7 2245    0 0.0031083481
## E    0    1    0    5 2519 0.0023762376
```

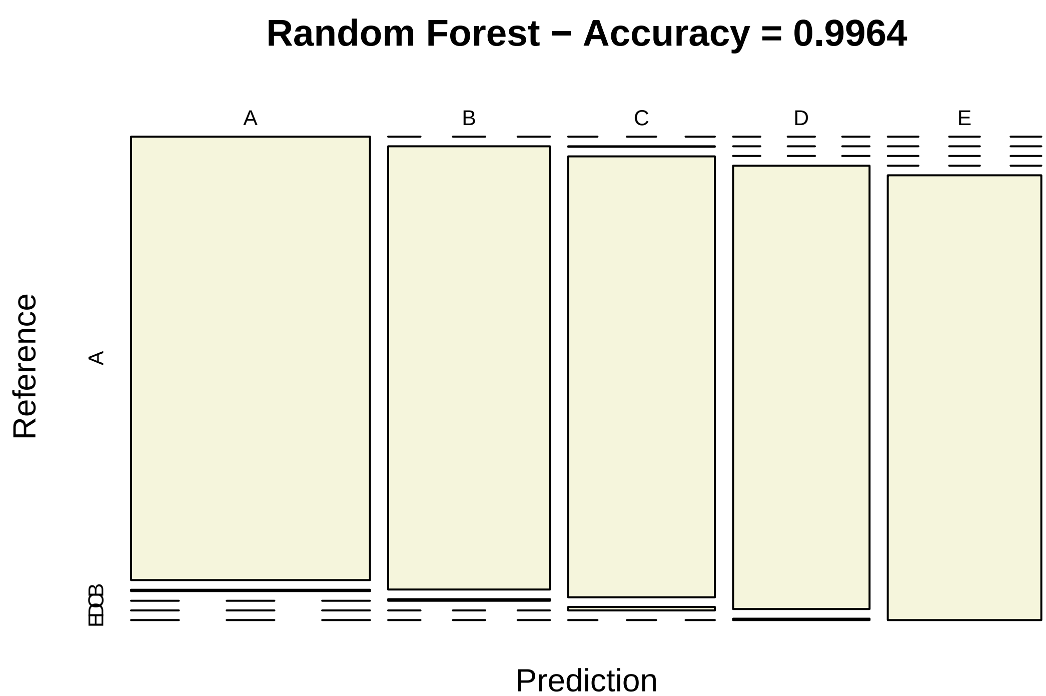
Predict on test dataset

```
predictRandForest <- predict(modFitRandForest, newdata=TestSet)
confMatRandForest <- confusionMatrix(predictRandForest, TestSet$classe)
confMatRandForest
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1674    5    0    0    0
##          B    0 1133    4    0    0
##          C    0    1 1022    8    0
##          D    0    0    0  956    3
##          E    0    0    0    0 1079
##
## Overall Statistics
##
##                Accuracy : 0.9964
##                  95% CI : (0.9946, 0.9978)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9955
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   0.9947   0.9961   0.9917   0.9972
## Specificity            0.9988   0.9992   0.9981   0.9994   1.0000
## Pos Pred Value         0.9970   0.9965   0.9913   0.9969   1.0000
## Neg Pred Value         1.0000   0.9987   0.9992   0.9984   0.9994
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2845   0.1925   0.1737   0.1624   0.1833
## Detection Prevalence   0.2853   0.1932   0.1752   0.1630   0.1833
## Balanced Accuracy      0.9994   0.9969   0.9971   0.9955   0.9986
```

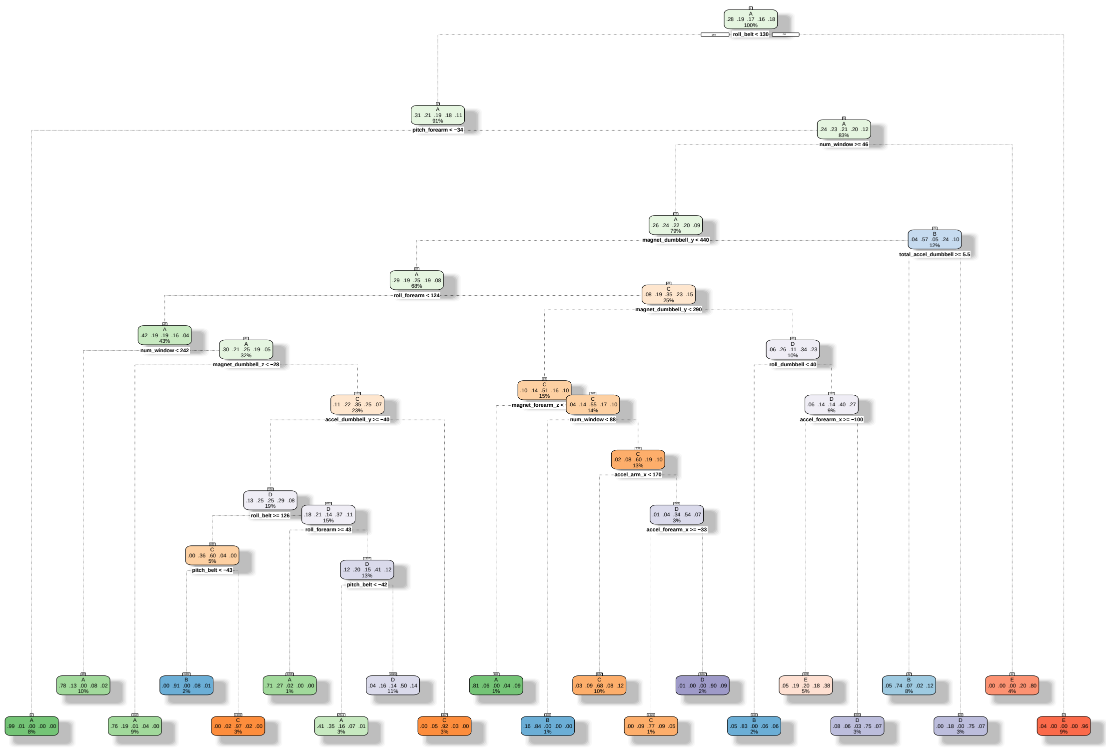
Ploting Matrix Results to Random Forest Model

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



Decision Trees Method

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



Rattle 2016−jul−30 18:00:23 delermando

Again, Predict on test dataset

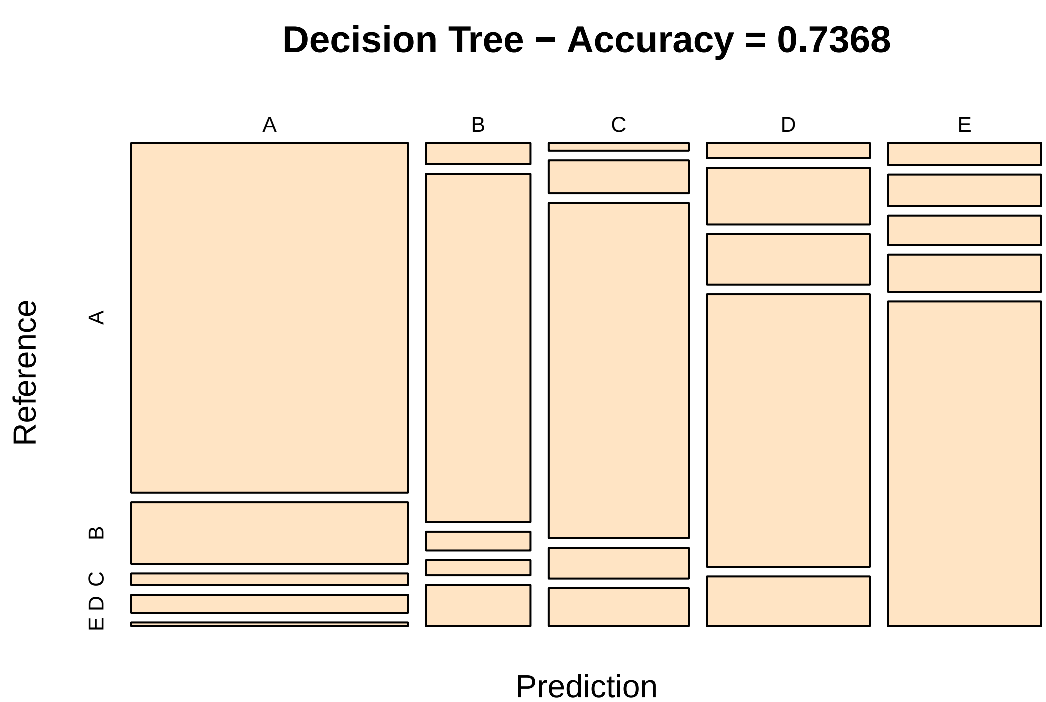
```
predictDecTree <- predict(modFitDecTree, newdata=TestSet, type="class")
confMatDecTree <- confusionMatrix(predictDecTree, TestSet$classe)
confMatDecTree
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1530  269   51   79   16
##          B   35  575   31   25   68
##          C   17   73  743   68   84
##          D   39  146  130  702  128
##          E   53   76   71   90  786
##
## Overall Statistics
##
##                Accuracy : 0.7368
##                  95% CI : (0.7253, 0.748)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.6656
##  Mcnemar's Test P-Value : < 2.2e-16
##
```

```
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9140  0.50483   0.7242   0.7282   0.7264
## Specificity            0.9014  0.96650   0.9502   0.9100   0.9396
## Pos Pred Value         0.7866  0.78338   0.7543   0.6131   0.7305
## Neg Pred Value         0.9635  0.89051   0.9422   0.9447   0.9384
## Prevalence             0.2845  0.19354   0.1743   0.1638   0.1839
## Detection Rate         0.2600  0.09771   0.1263   0.1193   0.1336
## Detection Prevalence   0.3305  0.12472   0.1674   0.1946   0.1828
## Balanced Accuracy      0.9077  0.73566   0.8372   0.8191   0.8330
```

As before, Ploting Matrix Results

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



Trying to Generalized Boosted Model

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

```
## Loading required package: gbm

## Warning: package 'gbm' was built under R version 3.3.1

## Loading required package: survival

##
## Attaching package: 'survival'

## The following object is masked from 'package:caret':
##
##     cluster

## Loading required package: splines

## Loading required package: parallel

## Loaded gbm 2.1.1

## Loading required package: plyr
```

```
modFitGBM$finalModel
```

```
## A gradient boosted model with multinomial loss function.
## 150 iterations were performed.
## There were 53 predictors of which 43 had non-zero influence.
```

Need to Predict on test dataset for GBM

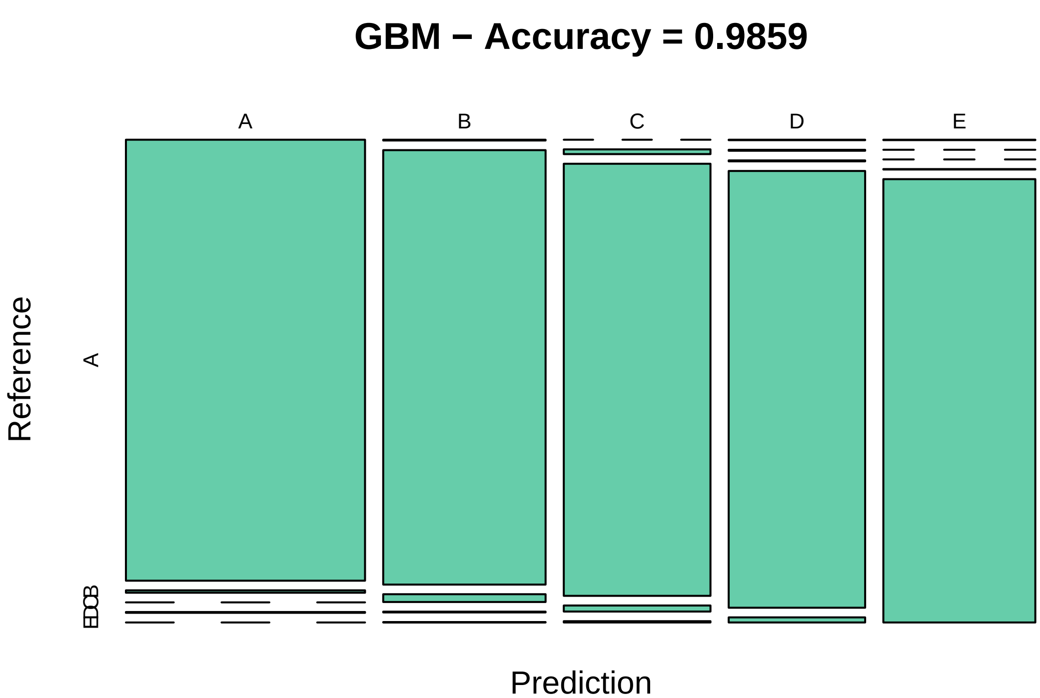
```
predictGBM <- predict(modFitGBM, newdata=TestSet)
confMatGBM <- confusionMatrix(predictGBM, TestSet$classe)
confMatGBM
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1670    9    0    3    0
##          B    2 1117   20    2    1
##          C    0   11 1004   14    3
##          D    1    2    2  944   11
##          E    1    0    0    1 1067
##
## Overall Statistics
##
##                Accuracy : 0.9859
##                  95% CI : (0.9825, 0.9888)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9822
```

```
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9976   0.9807   0.9786   0.9793   0.9861
## Specificity            0.9972   0.9947   0.9942   0.9967   0.9996
## Pos Pred Value         0.9929   0.9781   0.9729   0.9833   0.9981
## Neg Pred Value         0.9990   0.9954   0.9955   0.9959   0.9969
## Prevalence             0.2845   0.1935   0.1743   0.1638   0.1839
## Detection Rate         0.2838   0.1898   0.1706   0.1604   0.1813
## Detection Prevalence   0.2858   0.1941   0.1754   0.1631   0.1816
## Balanced Accuracy      0.9974   0.9877   0.9864   0.9880   0.9929
```

plot matrix results

```
plot(confMatGBM$table, col = "aquamarine3",
     main = paste("GBM - Accuracy =", round(confMatGBM$overall['Accuracy'], 4)))
```



The accuracy of the 3 regression modeling methods above are:

Random Forest : 0.9963 Decision Tree : 0.7368 GBM : 0.9839

Cross Validation Model

We try to solve a classification problem, then we must trie to use the classification method, at this time we sill use caret package: classification tree algorithm and random force. I also carried out 3-fold validation using the trainControl function.

Preparing Data

```
training<-read.csv("pml-training.csv",na.strings=c("NA","#DIV/0!"))
testing<-read.csv("pml-testing.csv",na.strings=c("NA","#DIV/0!"))
table(training$classe)
```

```
##
##    A    B    C    D    E
## 5580 3797 3422 3216 3607
```

```
NA_Count = sapply(1:dim(training)[2],function(x)sum(is.na(training[,x])))
NA_list = which(NA_Count>0)
colnames(training[,c(1:7)])
```

```
## [1] "X"                    "user_name"            "raw_timestamp_part_1"
## [4] "raw_timestamp_part_2" "cvtd_timestamp"       "new_window"
## [7] "num_window"
```

```
training = training[,-NA_list]
training = training[,-c(1:7)]
training$classe = factor(training$classe)
testing = testing[,-NA_list]
testing = testing[,-c(1:7)]
```

The testing dataset has been processed in the same way

```
set.seed(1234)
cv3 = trainControl(method="cv",number=3,allowParallel=TRUE,verboseIter=TRUE)
modrf = train(classe~., data=training, method="rf",trControl=cv3)
```

```
## + Fold1: mtry= 2
## - Fold1: mtry= 2
## + Fold1: mtry=27
## - Fold1: mtry=27
## + Fold1: mtry=52
## - Fold1: mtry=52
## + Fold2: mtry= 2
## - Fold2: mtry= 2
## + Fold2: mtry=27
## - Fold2: mtry=27
## + Fold2: mtry=52
## - Fold2: mtry=52
## + Fold3: mtry= 2
## - Fold3: mtry= 2
## + Fold3: mtry=27
## - Fold3: mtry=27
## + Fold3: mtry=52
## - Fold3: mtry=52
## Aggregating results
## Selecting tuning parameters
## Fitting mtry = 2 on full training set
```

```r
modtree = train(classe~.,data=training,method="rpart",trControl=cv3)
```

```
## + Fold1: cp=0.03568
## - Fold1: cp=0.03568
## + Fold2: cp=0.03568
## - Fold2: cp=0.03568
## + Fold3: cp=0.03568
## - Fold3: cp=0.03568
## Aggregating results
## Selecting tuning parameters
## Fitting cp = 0.0357 on full training set
```

Now, we will verify the performance of these two model on the testing dataset

```r
prf=predict(modrf,training)
ptree=predict(modtree,training)
table(prf,training$classe); table(ptree,training$classe)
```

```
##
## prf    A    B    C    D    E
##   A 5580    0    0    0    0
##   B    0 3797    0    0    0
##   C    0    0 3422    0    0
##   D    0    0    0 3216    0
##   E    0    0    0    0 3607
```

```
##
## ptree    A    B    C    D    E
##     A 5080 1581 1587 1449  524
##     B   81 1286  108  568  486
##     C  405  930 1727 1199  966
##     D    0    0    0    0    0
##     E   14    0    0    0 1631
```

For the testing dataset.

```r
prf=predict(modrf,testing)
ptree=predict(modtree,testing)
table(prf,ptree)
```

```
##    ptree
## prf A B C D E
##   A 7 0 0 0 0
##   B 3 0 5 0 0
##   C 0 0 1 0 0
##   D 0 0 1 0 0
##   E 1 0 2 0 0
```

From the results, it appears that the random forest model has the best accuracy for testing datas

Conclusion

I think that random forest model to the testing dataset for submission result.

```
answers=predict(modrf,testing)
pml_write_files = function(x){
  n = length(x)
  for(i in 1:n){
    filename = paste0("problem_id_",i,".txt")
    write.table(x[i],file=filename,quote=FALSE,row.names=FALSE,col.names=FALSE)
  }
}
answers
```

```
##  [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
```

pml_write_files(answers)

Other conclusion is that 52 variables to build the random forest model with 3-fold cross validation. The out-of-sample error is approximately 0.9%.

The predicted classes for the 20 tests are: B A B A A E D B A A B C B A E E A B B B.