Prediction Assignment Writeup

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In this classification challenge we will use Random Forest, which has a great reputation in solving this type of problems.

As my PC has 8 available cores, we can profit from this by using parallel libraries together with other useful libs.

```
library(doParallel); library(parallel)
cores=detectCores()
clust = makeCluster(cores)
registerDoParallel(clust)
library(caret); library(kernlab); library(ISLR); library(RANN);
library(DMwR);library(MASS); library(randomForest); library(e1071)


train = read.csv(file="pml-training.csv", header = TRUE,  sep = ',')
test = read.csv(file="pml-testing.csv", header = TRUE,  sep = ',')

#In this report I will not execute these two commands for the sake of size
#summary(train)
#str(train)
```

It can be easily seen that the training data is far from being clean and ready for analysis. Lots of missing data and error values. Let’s try to clean it steadily. Firstly, we should label as NAs empty values, NAs itself, and also error messages “#DIV/0!”.

```
#In this report I will not execute these two commands for the sake of size
#summary(test)
#str(test)
```

The test set looks much cleaner. We will preserve its content.

Reloading training and testing sets.

```
train_v1 = read.csv(file="pml-training.csv", na.strings =c("NA", "", "#DIV/0!
"), header = TRUE,  sep = ',')
test_v1 = read.csv(file="pml-testing.csv", na.strings=c("NA", "", "#DIV/0!"),
 header = TRUE, sep = ',')

#Doing proper time formatting. Although, we will not use it in this project

train_v1$cvtd_timestamp = strptime(train_v1$cvtd_timestamp, "%d/%m/%Y %H:%M")
test_v1$cvtd_timestamp = strptime(test_v1$cvtd_timestamp, "%d/%m/%Y %H:%M")
train_v1$cvtd_timestamp = as.Date(train_v1$cvtd_timestamp)
test_v1$cvtd_timestamp = as.Date(test_v1$cvtd_timestamp)

#In this report I will not execute these four commands for the sake of size
#summary(train_v1)
#str(train_v1)
#summary(test_v1)
#str(test_v1)
```

Our version v1 looks better now. Our dataset has a lot of features. Perhaps, not all of them are useful. We shall try to truncate our list of features. One of the ideas would be excluding those features, which have a near zero variation. Let’s identify them and remove

```
#Removing near zero variation. V2

nearzero <- nearZeroVar(train_v1, saveMetrics = TRUE)
#nearzero
train_v2 <- train_v1[, !nearzero$nzv]

#str(train_v2)
```

Now we should get NAs sorted. Some of the columns are full of NAs and are of no use to us. I decided to remove those, which have a simple majority of NAs.

```
#Removing those with majorities of NA's. V3

NA_cleanup_train =  sapply(colnames(train_v2), function(x) if(sum(is.na(train
_v2[,x])) > 0.50*nrow(train_v2)) {return(TRUE)}else{return(FALSE)})

train_v3 = train_v2[,!NA_cleanup_train]

#In this report I will not execute these two commands for the sake of size
#str(train_v3)
#summary(train_v3)

#Checking if there any NA's left.
which(is.na(train_v3))
```

```
## integer(0)
```

For the remaining features we should find such, which are strongly correlated with each other. Obviously, we could play with PCA-method and reduce our features space. I will not do that. I will just exclude those, which correlation is exceeding 0.5. We should exclude from our consideration four variables: X, username, timing and classe. X is, in fact, very misguiding. If one uses it in a prediction model, it gives an accuracy of 100% for the training set. Most probably, it is due to the fact that all rows were collected sequently for every exercise class. Therefore, we should not use X, and also usernames and dates.

```
#Remove correlations. V4

features_corr <- findCorrelation(cor(train_v3[,-c(1,2,5,59)]), cutoff=0.5)
features_corr
```

```
##  [1] 13  4 12 25  7  6 39 11 14  5 32 40 38 41 33 42 50 24  1 37 55 26 28
## [24] 15 51 27 18 35 49 48 36 21
```

```
names(train_v3[, -c(1,2,5,59)])[features_corr]
```

```
##  [1] "accel_belt_z"         "roll_belt"            "accel_belt_y"
##  [4] "accel_arm_y"          "total_accel_belt"     "yaw_belt"
##  [7] "accel_dumbbell_z"     "accel_belt_x"         "magnet_belt_x"
## [10] "pitch_belt"           "yaw_dumbbell"         "magnet_dumbbell_x"
## [13] "accel_dumbbell_y"     "magnet_dumbbell_y"    "total_accel_dumbbell"
## [16] "magnet_dumbbell_z"    "accel_forearm_x"      "accel_arm_x"
## [19] "raw_timestamp_part_1" "accel_dumbbell_x"     "magnet_forearm_z"
## [22] "accel_arm_z"          "magnet_arm_y"         "magnet_belt_y"
## [25] "accel_forearm_y"      "magnet_arm_x"         "pitch_arm"
## [28] "gyros_dumbbell_y"     "gyros_forearm_z"      "gyros_forearm_y"
## [31] "gyros_dumbbell_z"     "gyros_arm_x"
```

```
train_v4 = train_v3[, -c(1,2,5,59)][,-features_corr]
train_v4$classe = train_v3[, 59]
str(train_v4)
```

```
## 'data.frame':    19622 obs. of  24 variables:
##  $ raw_timestamp_part_2: int  788290 808298 820366 120339 196328 304277 36
8296 440390 484323 484434 ...
##  $ num_window          : int  11 11 11 12 12 12 12 12 12 12 ...
##  $ gyros_belt_x        : num  0 0.02 0 0.02 0.02 0.02 0.02 0.02 0.02 0.03
...
##  $ gyros_belt_y        : num  0 0 0 0 0.02 0 0 0 0 0 ...
##  $ gyros_belt_z        : num  -0.02 -0.02 -0.02 -0.03 -0.02 -0.02 -0.02 -0
.02 -0.02 0 ...
##  $ magnet_belt_z       : int  -313 -311 -305 -310 -302 -312 -311 -313 -312
 -308 ...
##  $ roll_arm            : num  -128 -128 -128 -128 -128 -128 -128 -128 -128
 -128 ...
##  $ yaw_arm             : num  -161 -161 -161 -161 -161 -161 -161 -161 -161
 -161 ...
##  $ total_accel_arm     : int  34 34 34 34 34 34 34 34 34 34 ...
##  $ gyros_arm_y         : num  0 -0.02 -0.02 -0.03 -0.03 -0.03 -0.03 -0.02
-0.03 -0.03 ...
##  $ gyros_arm_z         : num  -0.02 -0.02 -0.02 0.02 0 0 0 0 -0.02 -0.02 .
..
##  $ magnet_arm_z        : int  516 513 513 512 506 513 509 510 518 516 ...
##  $ roll_dumbbell       : num  13.1 13.1 12.9 13.4 13.4 ...
##  $ pitch_dumbbell      : num  -70.5 -70.6 -70.3 -70.4 -70.4 ...
##  $ gyros_dumbbell_x    : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ roll_forearm        : num  28.4 28.3 28.3 28.1 28 27.9 27.9 27.8 27.7 2
7.7 ...
##  $ pitch_forearm       : num  -63.9 -63.9 -63.9 -63.9 -63.9 -63.9 -63.9 -6
3.8 -63.8 -63.8 ...
##  $ yaw_forearm         : num  -153 -153 -152 -152 -152 -152 -152 -152 -152
 -152 ...
##  $ total_accel_forearm : int  36 36 36 36 36 36 36 36 36 36 ...
##  $ gyros_forearm_x     : num  0.03 0.02 0.03 0.02 0.02 0.02 0.02 0.02 0.03
 0.02 ...
##  $ accel_forearm_z     : int  -215 -216 -213 -214 -214 -215 -215 -213 -214
 -215 ...
##  $ magnet_forearm_x    : int  -17 -18 -18 -16 -17 -9 -18 -9 -16 -22 ...
##  $ magnet_forearm_y    : num  654 661 658 658 655 660 659 660 653 656 ...
##  $ classe              : Factor w/ 5 levels "A","B","C","D",..: 1 1 1 1 1
1 1 1 1 1 ...
```

The training set is simply too large. At this stage we will try to gently truncate it without loss of significance. Sampling of 10% from our training set should be enough. This we will justify by assessing our accuracy. The training subset of 10% we will split into 75% for training and 25% for testing.

```
table(train_v4$classe)
```

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

```
#It is noteworthy that the classes are not skewed, which is good
#so, we don't need to pick selectively every class...just taking random 10%

reduced_training_set = createDataPartition(y=train_v4$classe, p=0.10, list =
FALSE)

inTrain = createDataPartition(y=train_v4[reduced_training_set,]$classe, p=0.7
5, list = FALSE)

Train_v5 = train_v4[reduced_training_set,][inTrain,]
Test_v5 = train_v4[reduced_training_set,][-inTrain,]
```

It is very helpful to see what features influence the accuracy. Let’s take a look at them.

```
#str(Train_v5)

control <- rfeControl(functions=rfFuncs, method="cv", number=10)
# run the RFE algorithm
results <- rfe(Train_v5[,-c(24)], Train_v5[,24], sizes=c(1:23), rfeControl=co
ntrol)
# summarize the results
print(results)
```

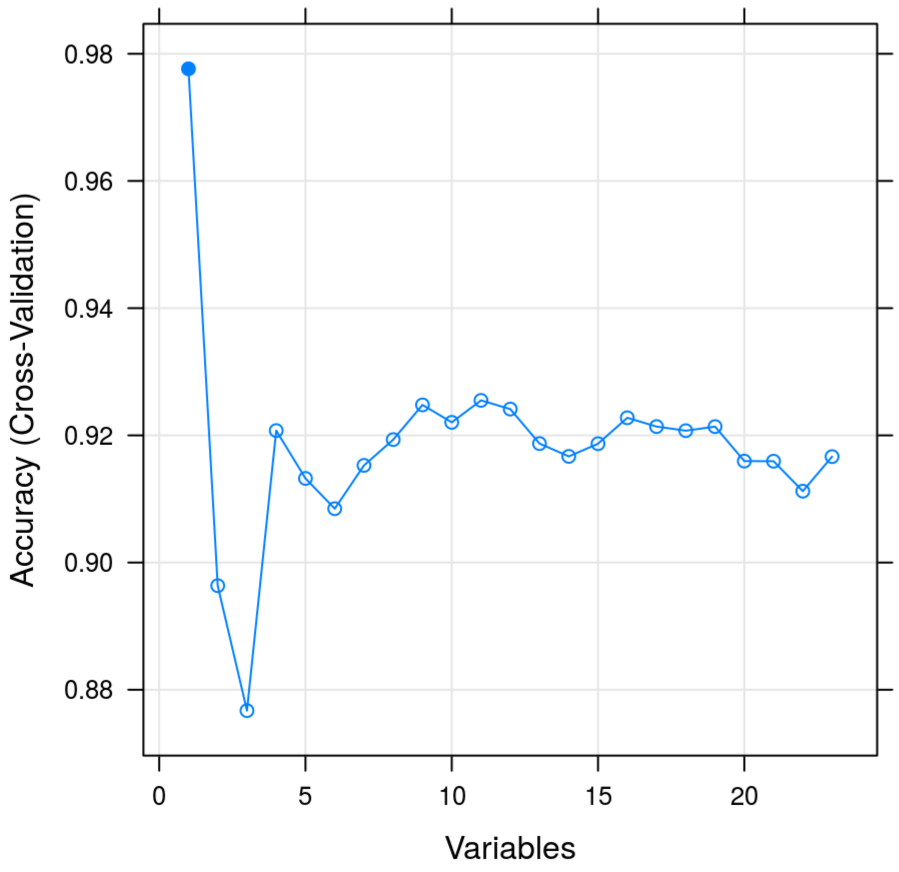
```
##
## Recursive feature selection
##
## Outer resampling method: Cross-Validated (10 fold)
##
## Resampling performance over subset size:
##
##  Variables Accuracy  Kappa AccuracySD KappaSD Selected
##          1   0.9776 0.9717    0.01110 0.01402        *
##          2   0.8964 0.8689    0.02785 0.03516
##          3   0.8767 0.8437    0.02674 0.03384
##          4   0.9208 0.8998    0.02340 0.02935
##          5   0.9132 0.8903    0.01417 0.01783
##          6   0.9085 0.8843    0.01846 0.02334
##          7   0.9153 0.8929    0.01421 0.01785
##          8   0.9193 0.8980    0.01758 0.02217
##          9   0.9248 0.9049    0.01300 0.01631
##         10   0.9220 0.9013    0.01657 0.02089
##         11   0.9255 0.9057    0.01960 0.02470
##         12   0.9241 0.9040    0.01738 0.02191
##         13   0.9187 0.8972    0.02474 0.03132
##         14   0.9167 0.8946    0.02080 0.02624
##         15   0.9187 0.8971    0.02170 0.02746
##         16   0.9228 0.9024    0.01976 0.02487
##         17   0.9214 0.9006    0.01911 0.02416
##         18   0.9207 0.8997    0.02285 0.02892
##         19   0.9214 0.9006    0.02043 0.02584
##         20   0.9160 0.8936    0.01913 0.02425
##         21   0.9159 0.8937    0.01970 0.02487
##         22   0.9112 0.8877    0.01989 0.02512
##         23   0.9167 0.8945    0.01753 0.02210
##
## The top 1 variables (out of 1):
##    num_window
```

```
# list the chosen features
predictors(results)
```

```
## [1] "num_window"
```

```
# plot the results

plot(results, type=c("g", "o"))
```



We will try here to compare TOP 7, TOP 10, and the full list of features(23)

```
control <- trainControl(method="cv", number=10, repeats=5)
#str(Train_v5)

model_RF_FULL = train(classe~., data=Train_v5, method="rf", preProcess="range
", trControl=control, tuneGrid = expand.grid(.mtry = c(2:6)),  n.tree=200, ma
xit=2000)

PREDICTION_FULL = predict(model_RF_FULL, newdata=Test_v5)
confusionMatrix(PREDICTION_FULL,Test_v5[,"classe"])
```

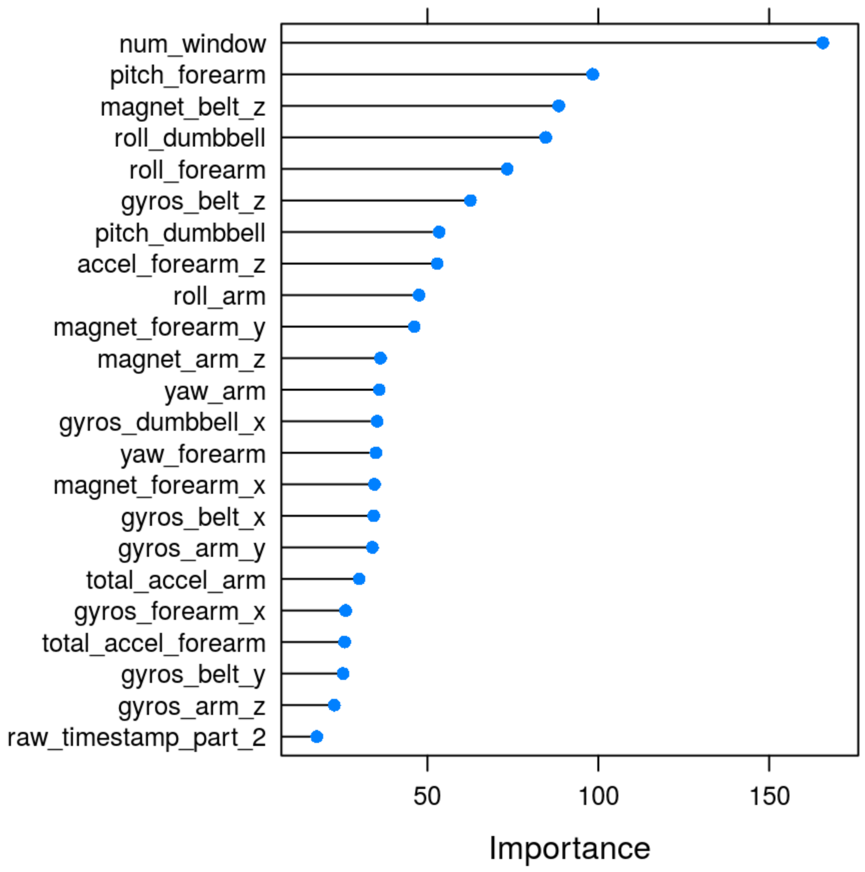
```
## Confusion Matrix and Statistics
## 
##           Reference
## Prediction   A   B   C   D   E
##          A 137   5   0   2   0
##          B   2  82   4   0   3
##          C   0   3  81  10   0
##          D   0   2   0  68   1
##          E   0   3   0   0  86
## 
## Overall Statistics
##                                           
##                Accuracy : 0.9284          
##                  95% CI : (0.9019, 0.9496)
##     No Information Rate : 0.2843          
##     P-Value [Acc > NIR] : < 2.2e-16       
##                                           
##                   Kappa : 0.9093          
##  Mcnemar's Test P-Value : NA              
## 
## Statistics by Class:
## 
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9856   0.8632   0.9529   0.8500   0.9556
## Specificity            0.9800   0.9772   0.9678   0.9927   0.9925
## Pos Pred Value         0.9514   0.9011   0.8617   0.9577   0.9663
## Neg Pred Value         0.9942   0.9673   0.9899   0.9713   0.9900
## Prevalence             0.2843   0.1943   0.1738   0.1636   0.1840
## Detection Rate         0.2802   0.1677   0.1656   0.1391   0.1759
## Detection Prevalence   0.2945   0.1861   0.1922   0.1452   0.1820
## Balanced Accuracy      0.9828   0.9202   0.9604   0.9213   0.9740
```

Let’s see the importance of features and try to select TOP 7 and TOP10. This will reduce our training set significantly.

```
importance <- varImp(model_RF_FULL, scale=FALSE)
# summarize importance
print(importance )
```

```
## rf variable importance
##
##   only 20 most important variables shown (out of 23)
##
##                     Overall
## num_window           165.71
## pitch_forearm         98.36
## magnet_belt_z         88.42
## roll_dumbbell         84.60
## roll_forearm          73.35
## gyros_belt_z          62.57
## pitch_dumbbell        53.40
## accel_forearm_z       52.84
## roll_arm              47.52
## magnet_forearm_y      46.16
## magnet_arm_z          36.28
## yaw_arm               35.89
## gyros_dumbbell_x      35.26
## yaw_forearm           34.93
## magnet_forearm_x      34.50
## gyros_belt_x          34.28
## gyros_arm_y           33.89
## total_accel_arm       30.03
## gyros_forearm_x       26.06
## total_accel_forearm   25.74
```

```
plot(importance)
```



Let’s see how accurate they are. We will constract predictors based on TOP 7 and TOP 10 features.

```
TOP7_features = c("num_window","pitch_forearm","magnet_belt_z","roll_dumbbell
","roll_forearm", "gyros_belt_z", "pitch_dumbbell", "accel_forearm_z", "class
e")
TOP10_features = c("num_window","pitch_forearm","magnet_belt_z","roll_dumbbel
l","roll_forearm", "gyros_belt_z", "pitch_dumbbell", "accel_forearm_z","roll_
arm", "magnet_forearm_y", "magnet_arm_z","classe")

model_RF_TOP7 = train(classe~., data=Train_v5[,TOP7_features], method="rf", p
reProcess="range", trControl=control, tuneGrid = expand.grid(.mtry = c(2:6)),
  n.tree=200, maxit=2000)
model_RF_TOP10 = train(classe~., data=Train_v5[,TOP10_features], method="rf",
 preProcess="range", trControl=control, tuneGrid = expand.grid(.mtry = c(2:6)
),  n.tree=200, maxit=2000)

#model_nnet_TOP7 = train(classe~., data=Train_v5[,TOP7_features], method="avN
Net", preProcess="range", trControl=control, tuneLength=4, maxit=2000 )

#PREDICTION_nnet_TOP7 = predict(model_nnet_TOP7, newdata=Test_v5)
#confusionMatrix(PREDICTION_nnet_TOP7,Test_v5[,"classe"])

PREDICTION_TOP7 = predict(model_RF_TOP7, newdata=Test_v5)
confusionMatrix(PREDICTION_TOP7,Test_v5[,"classe"])
```

```
## Confusion Matrix and Statistics
## 
##           Reference
## Prediction   A   B   C   D   E
##          A 134   5   0   2   0
##          B   4  85   3   2   0
##          C   0   2  81   1   0
##          D   1   2   0  74   5
##          E   0   1   1   1  85
## 
## Overall Statistics
## 
##                Accuracy : 0.9387
##                  95% CI : (0.9136, 0.9582)
##     No Information Rate : 0.2843
##     P-Value [Acc > NIR] : < 2.2e-16
## 
##                   Kappa : 0.9224
##  Mcnemar's Test P-Value : NA
## 
## Statistics by Class:
## 
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9640   0.8947   0.9529   0.9250   0.9444
## Specificity            0.9800   0.9772   0.9926   0.9804   0.9925
## Pos Pred Value         0.9504   0.9043   0.9643   0.9024   0.9659
## Neg Pred Value         0.9856   0.9747   0.9901   0.9853   0.9875
## Prevalence             0.2843   0.1943   0.1738   0.1636   0.1840
## Detection Rate         0.2740   0.1738   0.1656   0.1513   0.1738
## Detection Prevalence   0.2883   0.1922   0.1718   0.1677   0.1800
## Balanced Accuracy      0.9720   0.9359   0.9728   0.9527   0.9685
```

```
PREDICTION_TOP10 = predict(model_RF_TOP10, newdata=Test_v5)
confusionMatrix(PREDICTION_TOP10,Test_v5[,"classe"])
```

```
## Confusion Matrix and Statistics
## 
##           Reference
## Prediction   A   B   C   D   E
##          A 135   6   0   1   0
##          B   4  82   5   1   0
##          C   0   5  79   4   0
##          D   0   2   0  72   3
##          E   0   0   1   2  87
## 
## Overall Statistics
## 
##                Accuracy : 0.9305
##                  95% CI : (0.9042, 0.9514)
##     No Information Rate : 0.2843
##     P-Value [Acc > NIR] : < 2.2e-16
## 
##                   Kappa : 0.912
##  Mcnemar's Test P-Value : NA
## 
## Statistics by Class:
## 
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9712   0.8632   0.9294   0.9000   0.9667
## Specificity            0.9800   0.9746   0.9777   0.9878   0.9925
## Pos Pred Value         0.9507   0.8913   0.8977   0.9351   0.9667
## Neg Pred Value         0.9885   0.9673   0.9850   0.9806   0.9925
## Prevalence             0.2843   0.1943   0.1738   0.1636   0.1840
## Detection Rate         0.2761   0.1677   0.1616   0.1472   0.1779
## Detection Prevalence   0.2904   0.1881   0.1800   0.1575   0.1840
## Balanced Accuracy      0.9756   0.9189   0.9536   0.9439   0.9796
```

```
PREDICTION_FULL = predict(model_RF_FULL, newdata=Test_v5)
confusionMatrix(PREDICTION_FULL,Test_v5[,"classe"])
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   A   B   C   D   E
##          A 132   6   0   1   0
##          B   4  82   8   0   3
##          C   0   6  73   3   1
##          D   3   1   2  74   1
##          E   0   0   2   2  85
##
## Overall Statistics
##
##                Accuracy : 0.9121
##                  95% CI : (0.8834, 0.9356)
##     No Information Rate : 0.2843
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.8888
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9496   0.8632   0.8588   0.9250   0.9444
## Specificity            0.9800   0.9619   0.9752   0.9829   0.9900
## Pos Pred Value         0.9496   0.8454   0.8795   0.9136   0.9551
## Neg Pred Value         0.9800   0.9668   0.9704   0.9853   0.9875
## Prevalence             0.2843   0.1943   0.1738   0.1636   0.1840
## Detection Rate         0.2699   0.1677   0.1493   0.1513   0.1738
## Detection Prevalence   0.2843   0.1984   0.1697   0.1656   0.1820
## Balanced Accuracy      0.9648   0.9125   0.9170   0.9539   0.9672
```

Accuracies for TOP7, TOP10 and TOP FULL are between 94 and 91%. It looks not bad, let’s see whether we can improve it. Before doing that, let’s see whether all three models do similar prediction for our test set.

```
PREDICTION_COURSE_TOP7 = predict(model_RF_TOP7, newdata=test_v1)

PREDICTION_COURSE_TOP10 = predict(model_RF_TOP10, newdata=test_v1)

PREDICTION_COURSE_FULL = predict(model_RF_FULL, newdata=test_v1)
```

comparing TOP7 to TOP10 and TOP10 to TOP FULL

```
table(PREDICTION_COURSE_TOP7, PREDICTION_COURSE_TOP10)
```

```
##                       PREDICTION_COURSE_TOP10
## PREDICTION_COURSE_TOP7 A B C D E
##                      A 7 0 0 0 0
##                      B 0 8 0 0 0
##                      C 0 0 1 0 0
##                      D 0 0 0 1 0
##                      E 0 0 0 0 3
```

```
table(PREDICTION_COURSE_TOP10, PREDICTION_COURSE_FULL)
```

```
##                        PREDICTION_COURSE_FULL
## PREDICTION_COURSE_TOP10 A B C D E
##                       A 7 0 0 0 0
##                       B 0 8 0 0 0
##                       C 0 0 1 0 0
##                       D 0 0 0 1 0
##                       E 0 0 0 0 3
```

According to what we see, we can rely on the model TOP7 as it does identical prediction as TOP10 and TOP FULL.

Thus, we should take a larger training set with less features (TOP 7). Therefore, training on more data with less features(TOP 7) is the best solution. This time we will sample 25% of the training set. It will improve our predictor and its accuracy

```
reduced_training_set_v2 = createDataPartition(y=train_v4$classe, p=0.25, list
 = FALSE)

inTrain = createDataPartition(y=train_v4[reduced_training_set_v2,]$classe, p=
0.75, list = FALSE)

Train_v666 = train_v4[reduced_training_set_v2,][inTrain,]
Test_v666 = train_v4[reduced_training_set_v2,][-inTrain,]

model_RF_TOP7_v2 = train(classe~., data=Train_v666[,TOP7_features], method="r
f", preProcess="range", trControl=control, tuneGrid = expand.grid(.mtry = c(2
:6)),  n.tree=200, maxit=2000)

PREDICTION_TOP7_v2 = predict(model_RF_TOP7_v2, newdata=Test_v666)
confusionMatrix(PREDICTION_TOP7_v2,Test_v666[,"classe"])
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   A   B   C   D   E
##          A 342   1   0   0   0
##          B   3 229   0   3   0
##          C   0   5 212   5   0
##          D   3   2   2 191   6
##          E   0   0   0   2 219
##
## Overall Statistics
##
##                Accuracy : 0.9739
##                  95% CI : (0.9633, 0.9821)
##     No Information Rate : 0.2841
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.967
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9828   0.9662   0.9907   0.9502   0.9733
## Specificity            0.9989   0.9939   0.9901   0.9873   0.9980
## Pos Pred Value         0.9971   0.9745   0.9550   0.9363   0.9910
## Neg Pred Value         0.9932   0.9919   0.9980   0.9902   0.9940
## Prevalence             0.2841   0.1935   0.1747   0.1641   0.1837
## Detection Rate         0.2792   0.1869   0.1731   0.1559   0.1788
## Detection Prevalence   0.2800   0.1918   0.1812   0.1665   0.1804
## Balanced Accuracy      0.9908   0.9801   0.9904   0.9688   0.9857
```

```
PREDICTION_COURSE_TOP7_v2 = predict(model_RF_TOP7_v2, newdata=test_v1)

table(PREDICTION_COURSE_TOP7_v2, PREDICTION_COURSE_FULL)
```

```
##                            PREDICTION_COURSE_FULL
## PREDICTION_COURSE_TOP7_v2 A B C D E
##                         A 7 0 0 0 0
##                         B 1 7 0 0 0
##                         C 0 0 1 0 0
##                         D 0 0 0 1 0
##                         E 0 0 0 0 3
```

```
PREDICTION_COURSE_TOP7_v2
```

```
##  [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
```

This table shows that our prediction didn’t change since the moment when we used only 10% of the training set. However, using 25% of the training set, we have achieved 97% of accuracy on the validation set. This is a very good result! And the last line shows our final prediction, which has been confirmed by quiz.