Prediction Assignment Writeup - Practical Machine Learning

nhatmn

Sunday, May 24, 2015

Data

The training data for this project are available here: https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv The test data are available here: https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv The data for this project come from this source: http://groupware.les.inf.puc-rio.br/har.

Load Load neccessary library

```
library("caret")
library("tree")
library("rattle")
library("randomForest")
library("rpart")
library("rpart.plot")
```

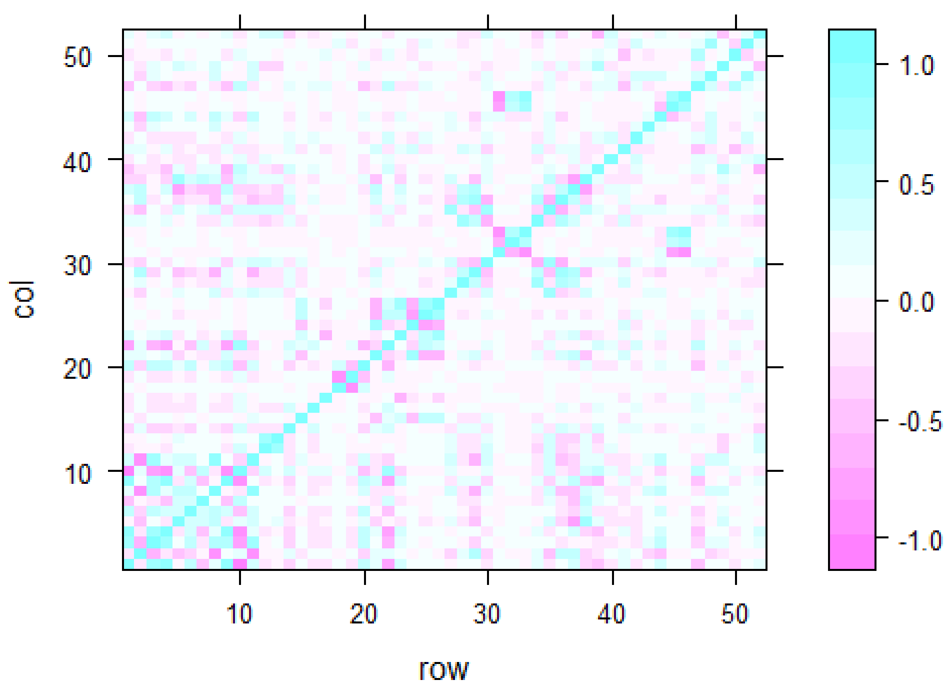
Read data from "pml-training.csv" and "pml-testing.csv".

```
# Load data
trainingOrg = read.csv("pml-training.csv", na.strings=c("", "NA", "NULL"))
testingOrg = read.csv("pml-testing.csv", na.strings=c("", "NA", "NULL"))

# Now see dimension of "pml-training.csv" and "pml-testing.csv".
dim(trainingOrg)

## [1] 19622   160

dim(testingOrg)

## [1]  20 160
```

Remove variables that have too many NA values

```
training.dena <- trainingOrg[ , colSums(is.na(trainingOrg)) == 0]
# Now see dimension of training.dena
dim(training.dena)
```

```
## [1] 19622    60

# Remove unrelevant variables.
remove = c('X', 'user_name', 'raw_timestamp_part_1', 'raw_timestamp_part_2',
'cvtd_timestamp', 'new_window', 'num_window')
training.dere <- training.dena[, -which(names(training.dena) %in% remove)]
dim(training.dere)

## [1] 19622    53

# Check the variables that have extremely low variance
zeroVar= nearZeroVar(training.dere[sapply(training.dere, is.numeric)],
saveMetrics = TRUE)
training.nonzerovar = training.dere[, zeroVar[, 'nzv']==0]
dim(training.nonzerovar)

## [1] 19622    53

# Remove highly correlated variables 90%
corrMatrix <- cor(na.omit(training.nonzerovar[sapply(training.nonzerovar,
is.numeric)]))
dim(corrMatrix)

## [1] 52 52

corrDF <- expand.grid(row = 1:52, col = 1:52)
corrDF$correlation <- as.vector(corrMatrix)

levelplot(correlation ~ row+ col, corrDF)
```



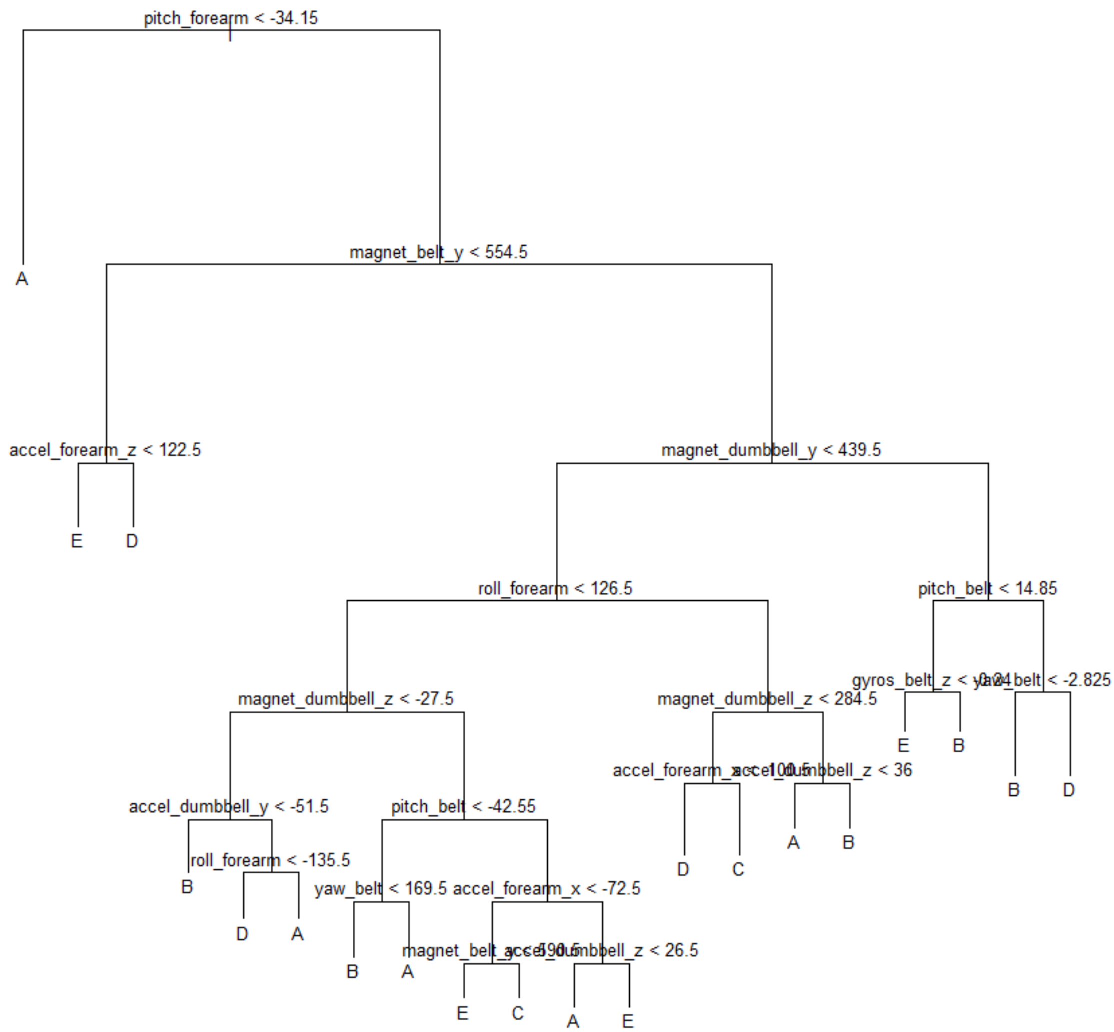
```r
# Remove high correlation variables.
removecor = findCorrelation(corrMatrix, cutoff = .90, verbose = TRUE)

training.decor = training.nonzerovar[, -removecor]
dim(training.decor)

## [1] 19622    46
```

Split data to training and testing for cross validation.

```r
inTrain <- createDataPartition(y=training.decor$classe, p=0.7, list=FALSE)
training <- training.decor[inTrain,]; testing <- training.decor[-inTrain,]
dim(training)

## [1] 13737    46

dim(testing)

## [1] 5885   46
```

Fit a tree to these data, and summarize and plot it

```r
set.seed(2125) #Birthday date of me and my girlfriend :)
tree.training=tree(classe~., data=training)
summary(tree.training)

## 
## Classification tree:
## tree(formula = classe ~ ., data = training)
## Variables actually used in tree construction:
##  [1] "pitch_forearm"     "magnet_belt_y"     "accel_forearm_z"  
##  [4] "magnet_dumbbell_y" "roll_forearm"      "magnet_dumbbell_z"
##  [7] "accel_dumbbell_y"  "pitch_belt"        "yaw_belt"         
## [10] "accel_forearm_x"   "accel_dumbbell_z"  "gyros_belt_z"     
## Number of terminal nodes:  20 
## Residual mean deviance:  1.677 = 23000 / 13720 
## Misclassification error rate: 0.3319 = 4559 / 13737

plot(tree.training)
text(tree.training, pretty=0, cex =.8)
```



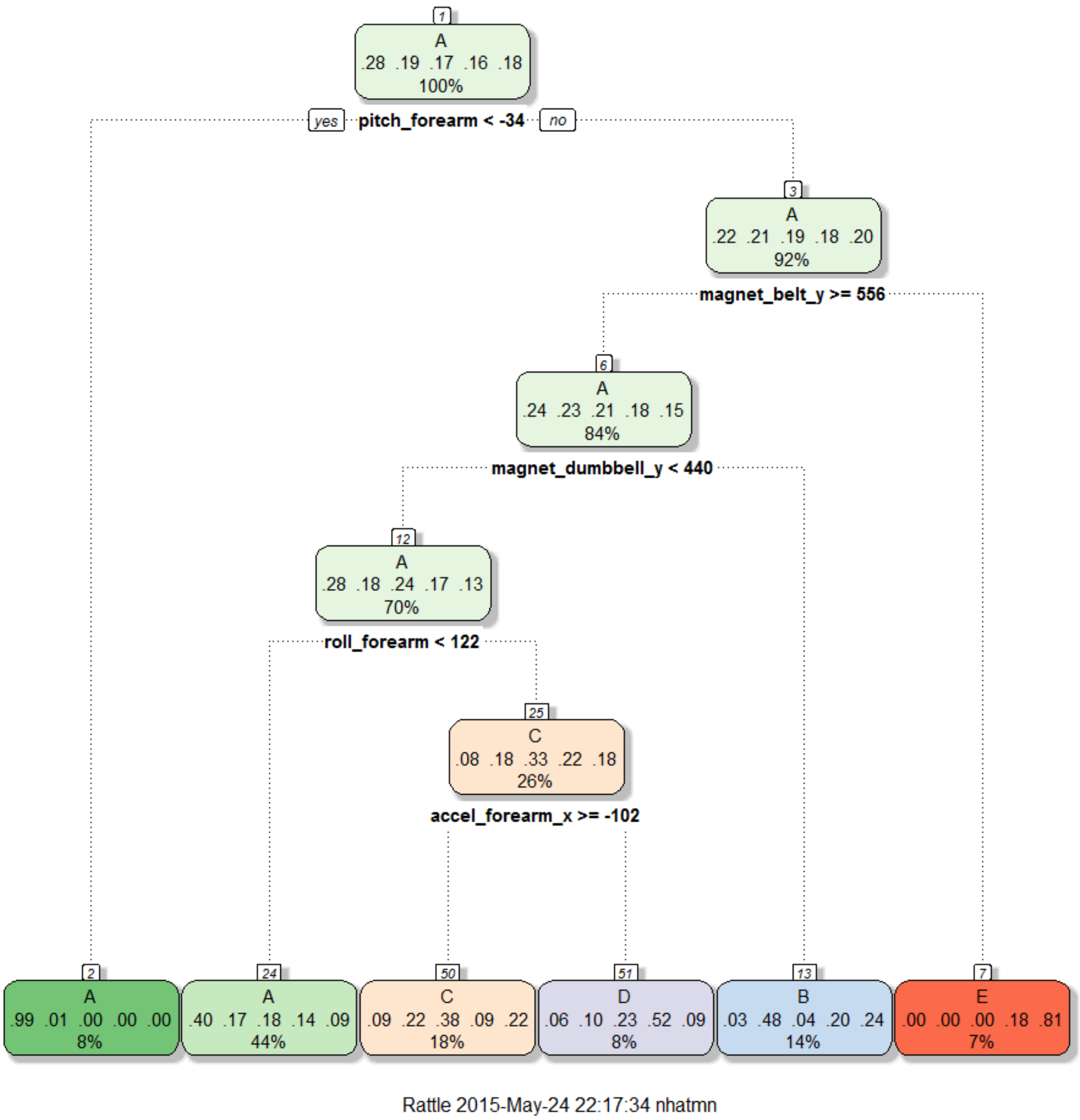
Running rpart for the form Caret

```
modFit <- train(classe ~ ., method="rpart", data=training)
print(modFit$finalModel)

## n= 13737
##
## node), split, n, loss, yval, (yprob)
##       * denotes terminal node
##
```

```
##  1) root 13737 9831 A (0.28 0.19 0.17 0.16 0.18)
##    2) pitch_forearm< -33.95 1114    8 A (0.99 0.0072 0 0 0) *
##    3) pitch_forearm>=-33.95 12623 9823 A (0.22 0.21 0.19 0.18 0.2)
##      6) magnet_belt_y>=555.5 11604 8807 A (0.24 0.23 0.21 0.18 0.15)
##       12) magnet_dumbbell_y< 439.5 9642 6906 A (0.28 0.18 0.24 0.17 0.13)
##         24) roll_forearm< 121.5 6051 3605 A (0.4 0.17 0.18 0.14 0.095) *
##         25) roll_forearm>=121.5 3591 2398 C (0.081 0.18 0.33 0.22 0.18)
##           50) accel_forearm_x>=-101.5 2494 1557 C (0.091 0.22 0.38 0.09
0.22) *
##           51) accel_forearm_x< -101.5 1097  525 D (0.057 0.099 0.23 0.52
0.088) *
##       13) magnet_dumbbell_y>=439.5 1962 1024 B (0.031 0.48 0.042 0.2 0.24)
*
##      7) magnet_belt_y< 555.5 1019  193 E (0.0029 0.002 0.00098 0.18 0.81)
*
```

Prettier plots

```
fancyRpartPlot(modFit$finalModel)
```



The result from 'caret' 'rpart' is close to 'tree'.

Check the performance of the tree on the testing data by cross validation.

```
tree.pred=predict(tree.training, testing,type="class")
predMatrix = with(testing, table(tree.pred, classe))
sum(diag(predMatrix))/sum(as.vector(predMatrix))

## [1] 0.6530161
```

```r
tree.pred=predict(modFit, testing)
predMatrix = with(testing,table(tree.pred, classe))
sum(diag(predMatrix))/sum(as.vector(predMatrix))
```

```
## [1] 0.4951572
```

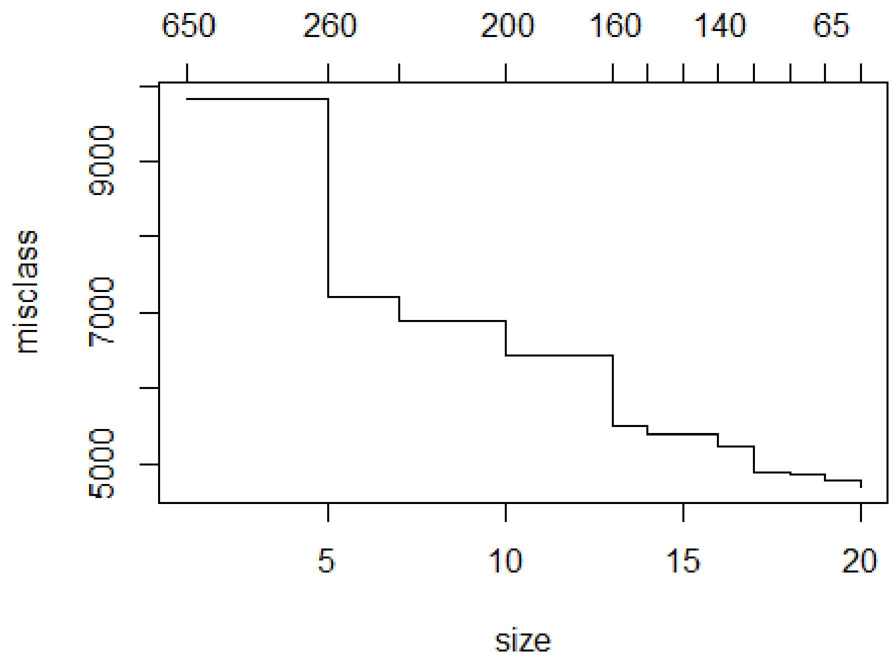
The result from 'caret' is much lower than the result from 'tree'.

Use Cross Validation to prune the tree

```r
cv.training=cv.tree(tree.training, FUN=prune.misclass)
cv.training
```

```
## $size
##  [1] 20 19 18 17 16 15 14 13 10  7  5  1
##
## $dev
##  [1] 4696 4769 4849 4886 5226 5399 5399 5508 6423 6889 7220 9831
##
## $k
##  [1]     -Inf  65.0000  80.0000 114.0000 140.0000 156.0000 157.0000
##  [8] 164.0000 200.6667 226.0000 260.5000 648.7500
##
## $method
## [1] "misclass"
##
## attr(,"class")
## [1] "prune"         "tree.sequence"
```

```r
plot(cv.training)
```



Suppose that the size of nodes is 19

```
# Suppose that the size of nodes is 19
prune.training=prune.misclass(tree.training, best=19)
# Evaluate this pruned tree on the test data
tree.pred=predict(prune.training, testing, type="class")
predMatrix = with(testing, table(tree.pred,classe))
sum(diag(predMatrix))/sum(as.vector(predMatrix))

## [1] 0.6499575
```

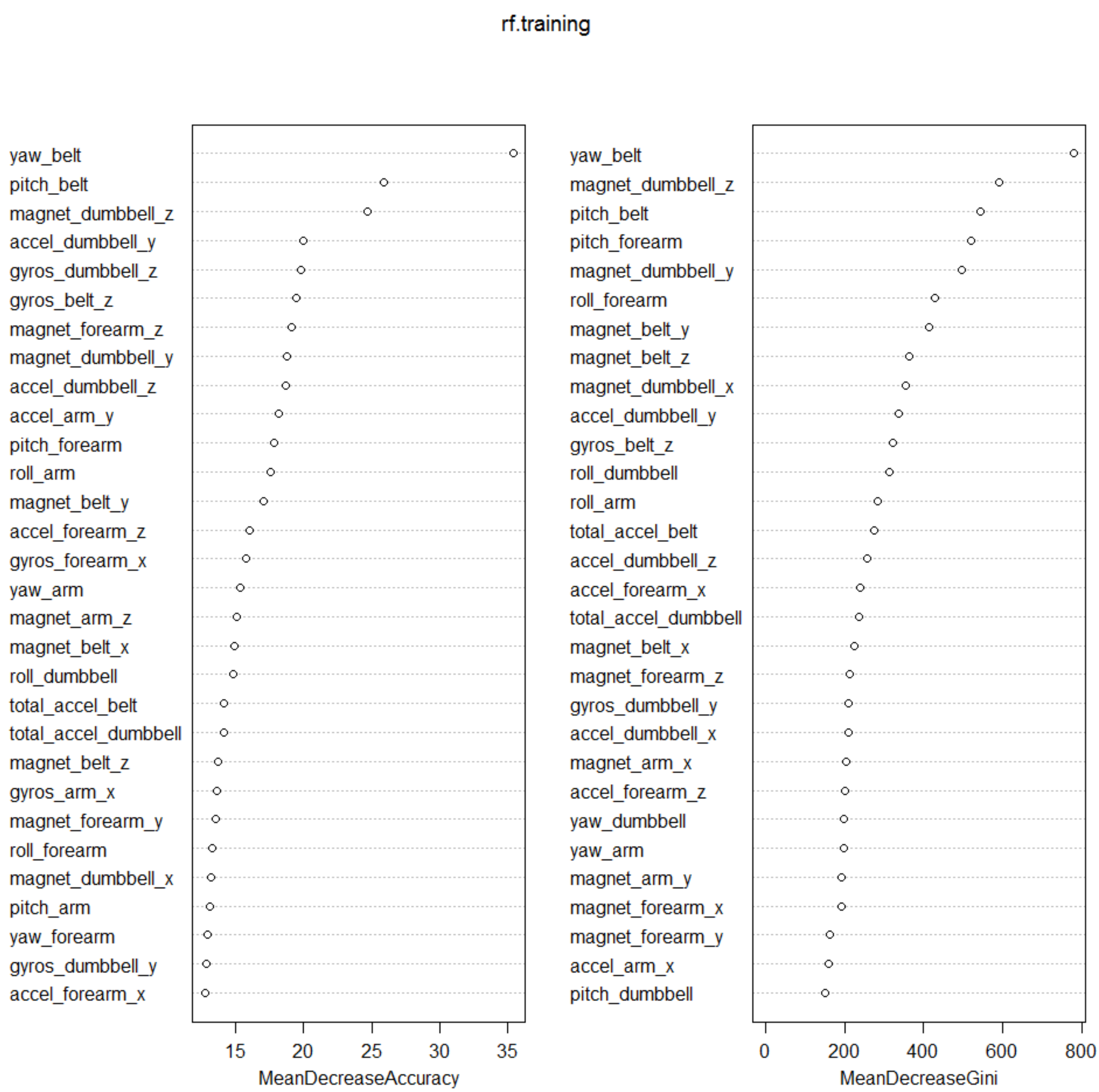
The single tree is not good enough, so we are going to use bootstrap to improve the accuracy. We are going to try random forests.

Random Forests

```
set.seed(2125) #Birthday date of me and my girlfriend :)
rf.training=randomForest(classe~., data=training, ntree=100, importance=TRUE)
rf.training

##
## Call:
##  randomForest(formula = classe ~ ., data = training, ntree = 100,
importance = TRUE)
##                Type of random forest: classification
##                      Number of trees: 100
## No. of variables tried at each split: 6
```

```
##
##         OOB estimate of  error rate: 0.63%
## Confusion matrix:
##      A    B    C    D    E class.error
## A 3902    1    1    0    2 0.001024066
## B   13 2635    9    0    1 0.008653123
## C    0   16 2376    4    0 0.008347245
## D    0    0   29 2221    2 0.013765542
## E    0    0    2    6 2517 0.003168317
```

```r
varImpPlot(rf.training,)
```



Evaluate this tree on the test data.

Our Random Forest model shows OOB estimate of error rate: 0.72% for the training data. Now we will predict it for out-of sample accuracy.

```
tree.pred=predict(rf.training, testing, type="class")
predMatrix = with(testing, table(tree.pred,classe))
sum(diag(predMatrix))/sum(as.vector(predMatrix))

## [1] 0.9940527
```

Conclusion: Predict the testing data from the website

```
answers <- predict(rf.training, testingOrg)
# See answers
answers

##  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20
##  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
```

Then print the result to files.

```
# Function to write "answers" vector to files
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)
    }
}
# Call the function to write "answers" vector to files
pml_write_files(answers)
```