Machine_learning

CW

15/04/2018

In this project, we aim to use data from accelerometers of 6 participants performing barbell lifts correctly and incorrectly in 5 different ways to predict how well they do it. outcome variable: classe * Class A - exactly according to the specification * Class B - throwing the elbows to the front * Class C - lifting the dumbbell only halfway * Class D - lowering the dumbbell only halfway * Class E - throwing the hips to the front

```
setwd("/Volumes/Daisy/R/R_assignmant/machine_learning/")
library(caret)
library(randomForest)
library(rpart)
library(rpart.plot)
```

```
trainingV <- read.csv("pml-training.csv",head=T)
testingo <- read.csv("pml-testing.csv",head=T)
set.seed(1121)
table(is.na(trainingV))
```

```
## 
##   FALSE    TRUE 
## 1852048 1287472
```

There many a lot of missing values, thus we first exclude variables with limited variance in prediction in training set. Same variables will be used in the testing set.

Preprocessing

1. exclude variables with many missing values. The “No.missingVar” variable will return number of missing values for all variables.

```
sum(is.na(trainingV))
```

```
## [1] 1287472
```

```
missingN<-matrix()

matName<-names(trainingV)
for (i in 1:dim(trainingV)[2]) {
   t<-sum(is.na(trainingV[,i]))
   missingN <- c(missingN,t)
}

missingN <- missingN[!is.na(missingN)]
```

```
No.missingVar <- data.frame(missingN, matName)
validVar<-No.missingVar[No.missingVar$missingN ==0,]
trainingV2 <- trainingV[names(trainingV) %in% validVar$matName]
trainingV3 <- trainingV2[,-c(1,2)]
```

2. The next step is to exclude variables with zero variance (little variance)

```
varT<-nearZeroVar(trainingV3,saveMetrics = T)
trainingV4<- trainingV3[,varT$nzv == FALSE]
```

3. Subsequently, the training dataset was seperated to a sub-training set and a validation set.

```
valida_index <- createDataPartition(trainingV4$classe, p =.75, list = FALSE)
validation <- trainingV4[-valida_index,]
training <- trainingV4[valida_index,]
testing <- testingo[,names(testingo) %in% names(training)]

dim(validation)

## [1] 4904   57

dim(training)

## [1] 14718    57

dim(testing)

## [1] 20 56
```

Creating models.

1. Here I tested three models, random forest ("rf"), rpart and gbm.

```
modf1 <- train(classe ~., training, method ="rf")
modf2 <- train (classe ~., training, method ="rpart")
modf3 <- train (classe ~., training, method ="gbm")
```

2. This is to predict test the model using the models created in the previous step on the validation set.

```
crossV1<- predict(modf1,newdata = validation)
crossV2<- predict(modf2,newdata = validation)
crossV3<- predict(modf3,newdata = validation)
```

3. To measure the model fit, using validation set:

```
confusionMatrix(crossV1,validation$classe)$overall

##       Accuracy          Kappa  AccuracyLower  AccuracyUpper   AccuracyNull
##      1.0000000      1.0000000      0.9992481      1.0000000      0.2844617
## AccuracyPValue  McnemarPValue
##      0.0000000            NaN

confusionMatrix(crossV2,validation$classe)$overall
```

```
##       Accuracy          Kappa  AccuracyLower  AccuracyUpper   AccuracyNull 
##   5.010196e-01   3.744276e-01   4.869265e-01   5.151114e-01   2.844617e-01 
## AccuracyPValue  McnemarPValue 
##  2.213235e-223            NaN 
```

```r
confusionMatrix(crossV3,validation$classe)$overall
```

```
##       Accuracy          Kappa  AccuracyLower  AccuracyUpper   AccuracyNull 
##      0.9973491      0.9966468      0.9954712      0.9985878      0.2844617 
## AccuracyPValue  McnemarPValue 
##      0.0000000            NaN 
```

Confusion Matrix shows that model 1 (random forest, method = "rf") and model 3 (medho = "gbm") accurately predict the validation dataset. We thus will apply the two models to the testing set.

Out of sample error rate for model 1 is 1-1.000 = 0, for model 3, out of sample error is 1 - .9973 =.0027

predicting the testing set

```r
predict(modf1,newdata=testing)
```

```
##  [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
```

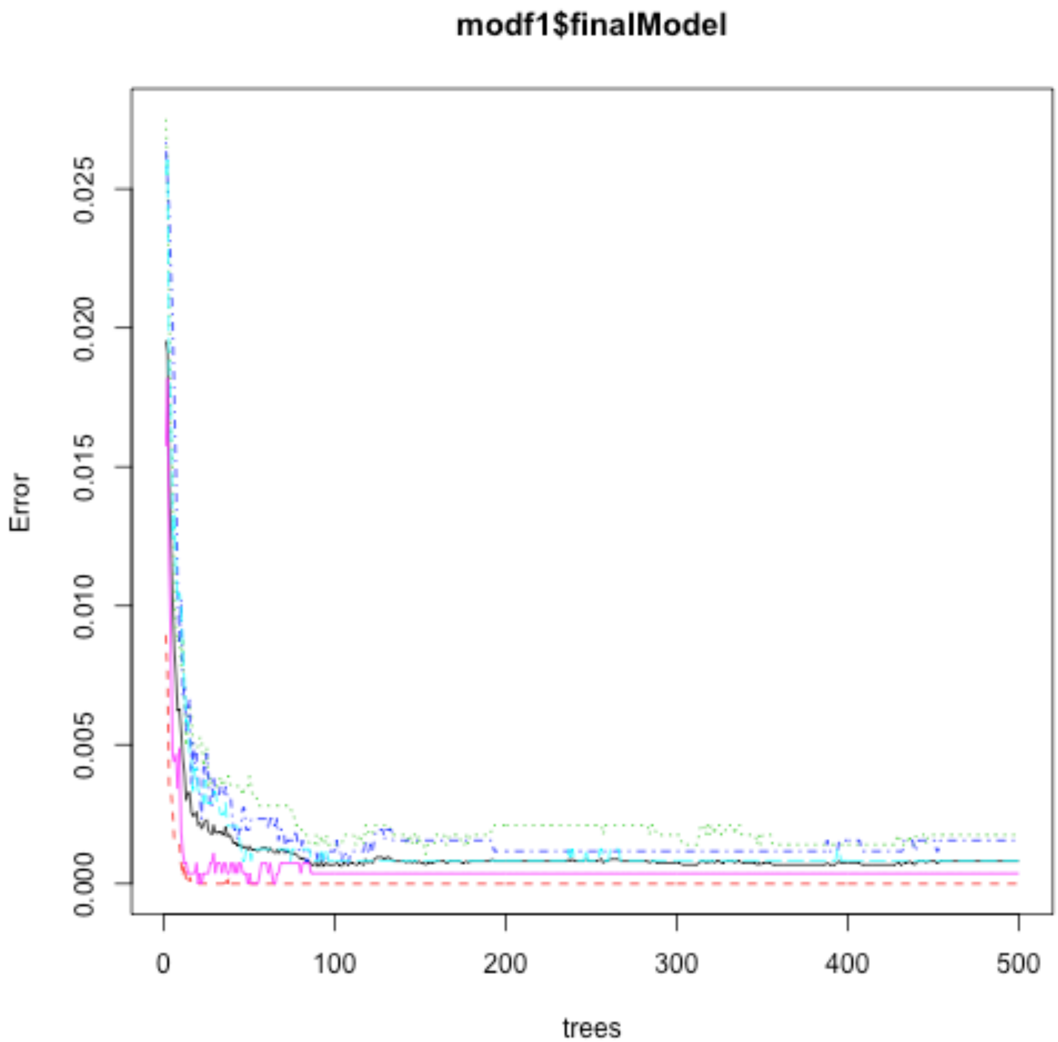
```r
predict(modf3,newdata=testing)
```

```
##  [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
```

The predictions made by the two models are identical

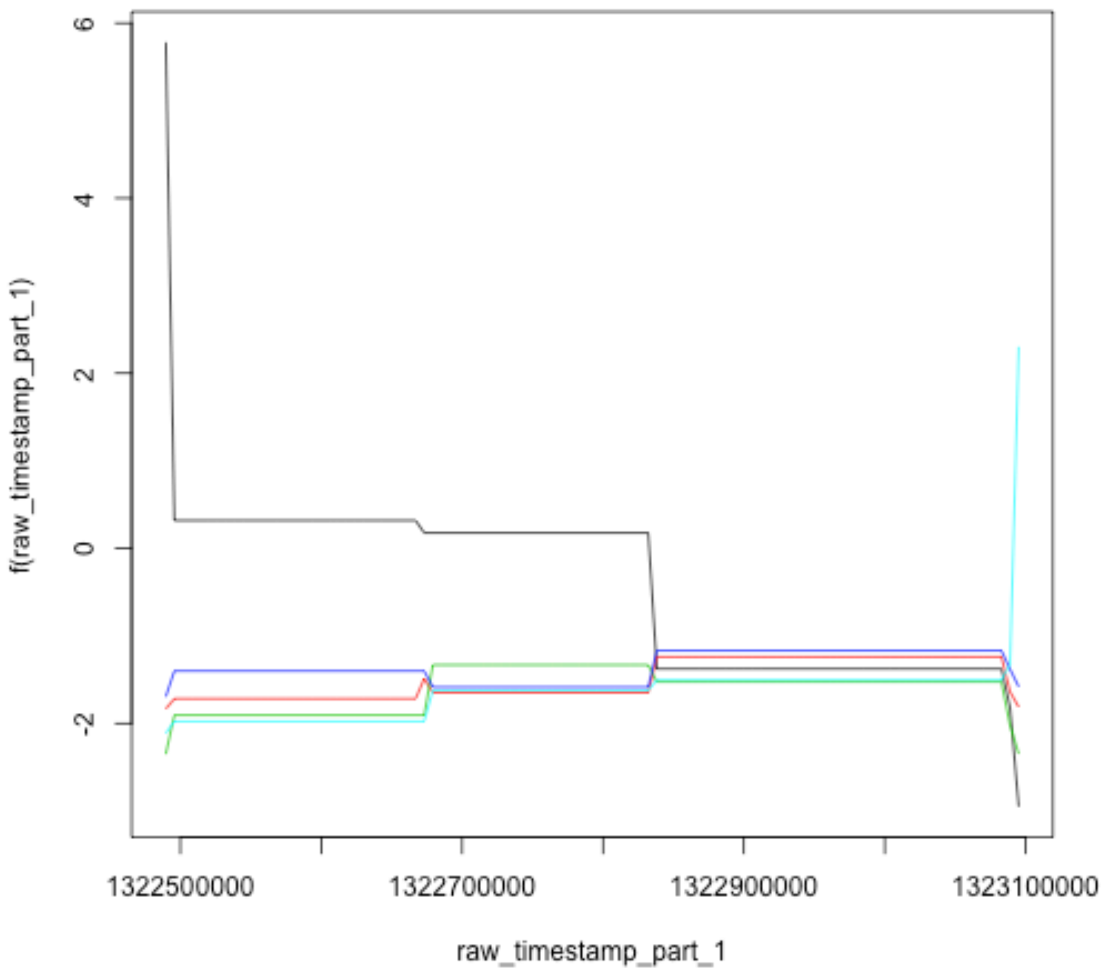
Appendix

```r
plot(modf1$finalModel)
```



plot of chunk unnamed-chunk-10

```
plot(modf3$finalModel)
```



plot of chunk unnamed-chunk-10