APA-L8

September 6, 2018

1 APA Laboratori 8 - Random Forests

In [1]:
```
# uncomment to install missing libraries
# install.packages("TunePareto")
#install.packages("tree")
#install.packages('randomForest')
```

In [2]:
```
options(repr.plot.width=6, repr.plot.height=6)
```

In [3]:
```
set.seed (6046)
```

1.1 Financial Example: classification model for deposit subscription

Direct marketing campaigns (phone calls) of a Portuguese banking institution. The classification goal is to predict if the client will subscribe a term deposit

In [4]:
```
deposit <- read.table ("bank-full.csv.gz",
                        header=TRUE,
                        stringsAsFactors=TRUE,
                        sep=";")

dim(deposit)
```

1. 45211 2. 17

In [5]:
```
summary(deposit)
```

```
      age                  job           marital          education
 Min.   :18.00   blue-collar:9732   divorced: 5207   primary  : 6851
 1st Qu.:33.00   management :9458   married :27214   secondary:23202
 Median :39.00   technician :7597   single  :12790   tertiary :13301
 Mean   :40.94   admin.     :5171                    unknown  : 1857
 3rd Qu.:48.00   services   :4154
 Max.   :95.00   retired    :2264
                 (Other)    :6835
 default        balance       housing      loan           contact
 no :44396   Min.   : -8019   no :20081   no :37967   cellular :29285
 yes:  815   1st Qu.:    72   yes:25130   yes: 7244   telephone: 2906
```

```
           Median :   448                             unknown  :13020
           Mean   :  1362
           3rd Qu.:  1428
           Max.   :102127

      day            month          duration         campaign
 Min.   : 1.00   may    :13766   Min.   :   0.0   Min.   : 1.000
 1st Qu.: 8.00   jul    : 6895   1st Qu.: 103.0   1st Qu.: 1.000
 Median :16.00   aug    : 6247   Median : 180.0   Median : 2.000
 Mean   :15.81   jun    : 5341   Mean   : 258.2   Mean   : 2.764
 3rd Qu.:21.00   nov    : 3970   3rd Qu.: 319.0   3rd Qu.: 3.000
 Max.   :31.00   apr    : 2932   Max.   :4918.0   Max.   :63.000
                 (Other): 6060
     pdays          previous          poutcome        y
 Min.   : -1.0   Min.   :  0.0000   failure: 4901   no :39922
 1st Qu.: -1.0   1st Qu.:  0.0000   other  : 1840   yes: 5289
 Median : -1.0   Median :  0.0000   success: 1511
 Mean   : 40.2   Mean   :  0.5803   unknown:36959
 3rd Qu.: -1.0   3rd Qu.:  0.0000
 Max.   :871.0   Max.   :275.0000
```

This dataset needs a lot of pre-processing ... also it displays a good mixture of categorical and numeric variables

age seems OK job has 12 values, let's check their frequency

seems OK

```
In [6]: table(deposit$job)
```

```
       admin.   blue-collar  entrepreneur     housemaid    management
         5171          9732          1487          1240          9458
      retired self-employed      services       student    technician
         2264          1579          4154           938          7597
   unemployed       unknown
         1303           288
```

education has 4 values, let's check their frequency

seems OK

```
In [7]: table(deposit$education)
```

```
  primary secondary  tertiary   unknown
     6851     23202     13301      1857
```

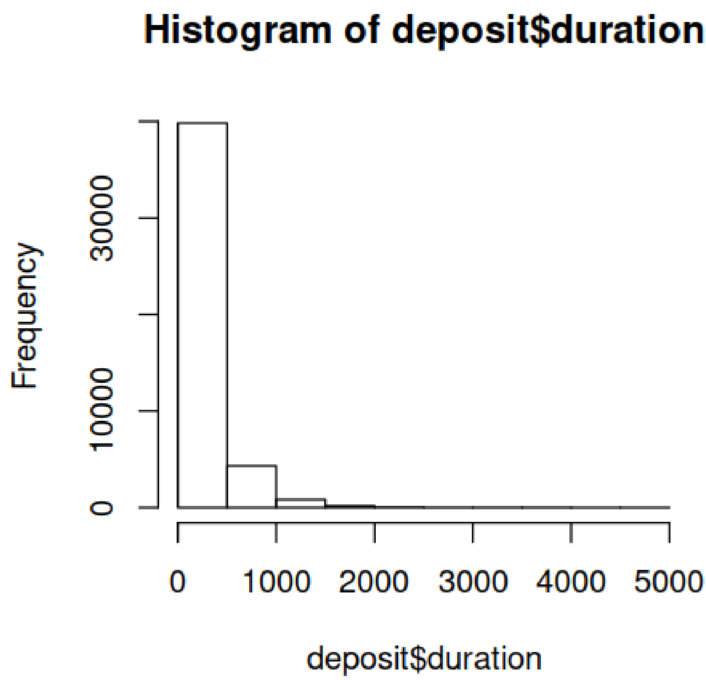
month looks very suspicious ... but is OK

```
In [8]: table(deposit$month)
```

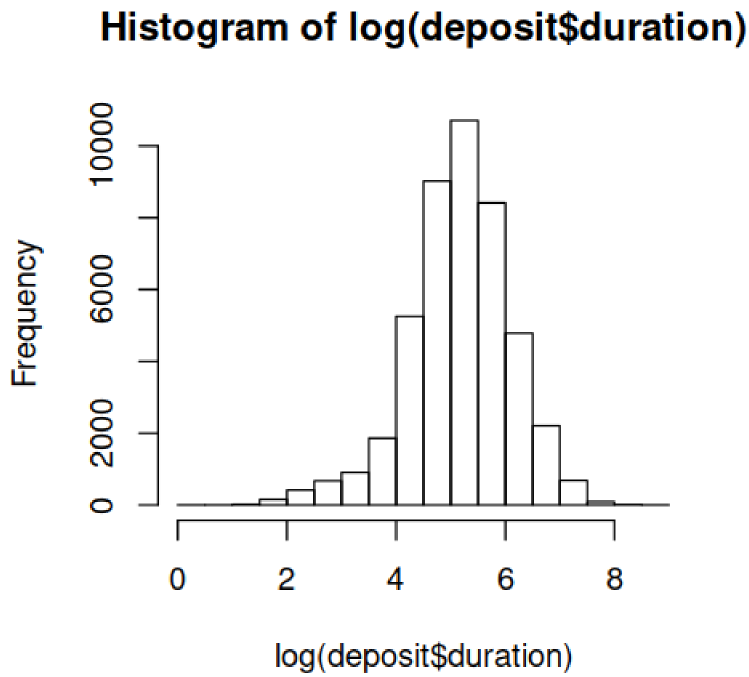
```
  apr   aug   dec   feb   jan   jul   jun   mar   may   nov   oct   sep
 2932  6247   214  2649  1403  6895  5341   477 13766  3970   738   579
```

Duration is highly skewed ...

```
In [9]: options(repr.plot.width=4, repr.plot.height=4)
        hist(deposit$duration)
```




```
In [10]: hist(log(deposit$duration))
```




```
In [11]: deposit$duration <- log(deposit$duration+0.001)
```

what to do with 'pdays' and 'previous'? it is not clear how to best pre-process them; we shall need some financial expertise... we leave them as they are

The rest seem OK (but it would take a careful analysis, and a lot of domain knowledge)

Let's rename the target ...

```
In [12]: colnames(deposit)[ncol(deposit)] <- "subscribed"

         dim(deposit)
```

1. 45211 2. 17

```
In [13]: summary(deposit)
```

```
      age                  job           marital          education    
 Min.   :18.00   blue-collar:9732   divorced: 5207   primary  : 6851  
 1st Qu.:33.00   management :9458   married :27214   secondary:23202  
 Median :39.00   technician :7597   single  :12790   tertiary :13301  
 Mean   :40.94   admin.     :5171                    unknown  : 1857  
 3rd Qu.:48.00   services   :4154                                     
 Max.   :95.00   retired    :2264                                     
                 (Other)    :6835                                     
```

```
 default        balance        housing      loan           contact
 no :44396   Min.   : -8019   no :20081   no :37967   cellular :29285
 yes:  815   1st Qu.:    72   yes:25130   yes: 7244   telephone: 2906
             Median :   448                           unknown  :13020
             Mean   :  1362
             3rd Qu.:  1428
             Max.   :102127

      day            month          duration          campaign
 Min.   : 1.00   may    :13766   Min.   :-6.908   Min.   : 1.000
 1st Qu.: 8.00   jul    : 6895   1st Qu.: 4.635   1st Qu.: 1.000
 Median :16.00   aug    : 6247   Median : 5.193   Median : 2.000
 Mean   :15.81   jun    : 5341   Mean   : 5.162   Mean   : 2.764
 3rd Qu.:21.00   nov    : 3970   3rd Qu.: 5.765   3rd Qu.: 3.000
 Max.   :31.00   apr    : 2932   Max.   : 8.501   Max.   :63.000
                 (Other): 6060
     pdays           previous          poutcome      subscribed
 Min.   : -1.0   Min.   :  0.0000   failure: 4901   no :39922
 1st Qu.: -1.0   1st Qu.:  0.0000   other  : 1840   yes: 5289
 Median : -1.0   Median :  0.0000   success: 1511
 Mean   : 40.2   Mean   :  0.5803   unknown:36959
 3rd Qu.: -1.0   3rd Qu.:  0.0000
 Max.   :871.0   Max.   :275.0000
```

Since we want to use different methods, we need CV and a separate test set:

In [14]:
```
library(TunePareto)
```

precalculate the TR/TE partition and the cross-validation partitions on the TR part

In [15]:
```
N <- nrow(deposit)
all.indexes <- 1:N

learn.indexes <- sample(1:N, round(2*N/3))
test.indexes <- all.indexes[-learn.indexes]

learn.data <- deposit[learn.indexes,]

nlearn <- length(learn.indexes)
ntest <- N - nlearn
```

First try a standard decision tree (CART)

In [16]:
```
library(tree)

model.tree <- tree (subscribed ~ ., data = learn.data)

summary(model.tree)
```

```
Classification tree:
tree(formula = subscribed ~ ., data = learn.data)
Variables actually used in tree construction:
[1] "duration" "poutcome" "month"    "contact"
Number of terminal nodes:  10
Residual mean deviance:  0.4841 = 14590 / 30130
Misclassification error rate: 0.1072 = 3232 / 30141
```

so training error rate is 10.72%

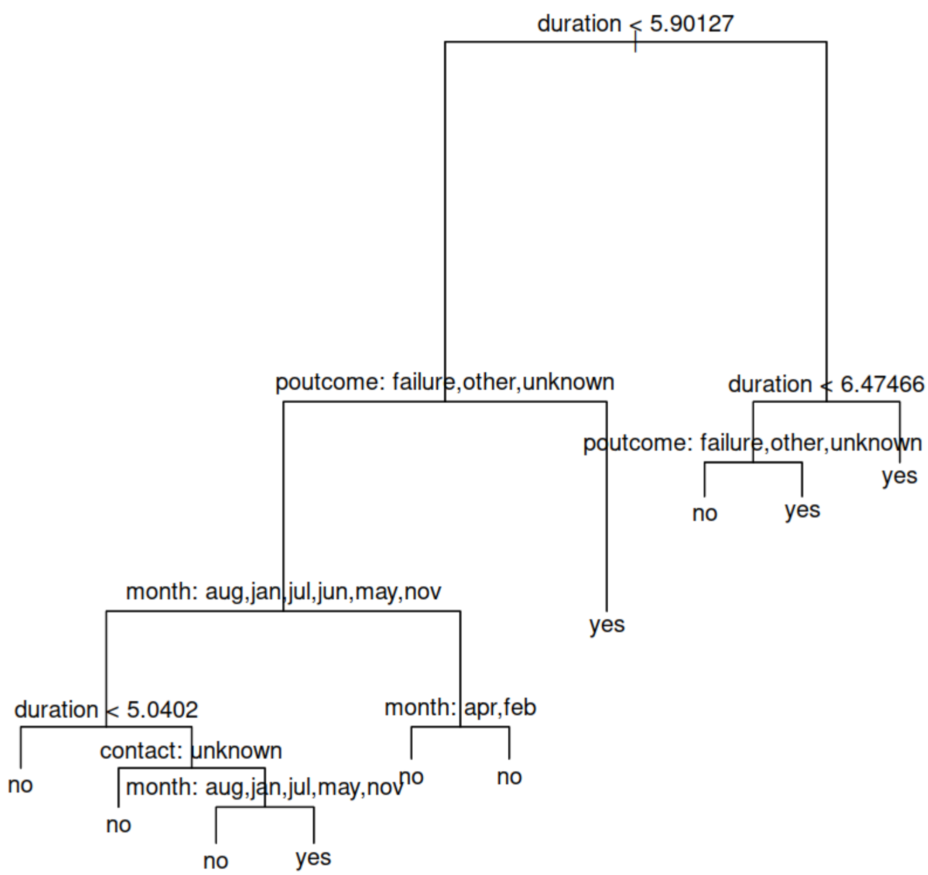
```
In [17]: model.tree
```

```
node), split, n, deviance, yval, (yprob)
      * denotes terminal node

 1) root 30141 21810.0 no ( 0.882519 0.117481 )
   2) duration < 5.90127 24030 11230.0 no ( 0.937578 0.062422 )
     4) poutcome: failure,other,unknown 23285  8590.0 no ( 0.954692 0.045308 )
       8) month: aug,jan,jul,jun,may,nov 19663  4527.0 no ( 0.975487 0.024513 )
        16) duration < 5.0402 10748   904.1 no ( 0.992929 0.007071 ) *
        17) duration > 5.0402 8915  3302.0 no ( 0.954459 0.045541 )
          34) contact: unknown 3269   124.1 no ( 0.997247 0.002753 ) *
          35) contact: cellular,telephone 5646  2873.0 no ( 0.929685 0.070315 )
            70) month: aug,jan,jul,may,nov 5456  2329.0 no ( 0.944831 0.055169 ) *
            71) month: jun 190   263.4 yes ( 0.494737 0.505263 ) *
       9) month: apr,dec,feb,mar,oct,sep 3622  3163.0 no ( 0.841800 0.158200 )
        18) month: apr,feb 2775  1824.0 no ( 0.898378 0.101622 ) *
        19) month: dec,mar,oct,sep 847  1090.0 no ( 0.656434 0.343566 ) *
     5) poutcome: success 745  1004.0 yes ( 0.402685 0.597315 ) *
   3) duration > 5.90127 6111  7785.0 no ( 0.666012 0.333988 )
     6) duration < 6.47466 3953  4323.0 no ( 0.763724 0.236276 )
      12) poutcome: failure,other,unknown 3761  3853.0 no ( 0.791279 0.208721 ) *
      13) poutcome: success 192   204.2 yes ( 0.223958 0.776042 ) *
     7) duration > 6.47466 2158  2990.0 yes ( 0.487025 0.512975 ) *
```

```
In [18]: options(repr.plot.width=8, repr.plot.height=8)
         plot (model.tree)

         text (model.tree,pretty=0)
```




```
In [19]: pred.tree <- predict (model.tree, deposit[test.indexes,], type="class")

         (ct <- table(Truth=deposit$subscribed[test.indexes], Pred=pred.tree))
```

```
     Pred
Truth    no   yes
  no  12601   721
  yes   897   851
```

We define now a convenience function (the harmonic mean), to compute the F1 accuracy:

```
In [20]: harm <- function (a,b) { 2/(1/a+1/b) }
```

percent by class

```
In [21]: prop.table(ct, 1)
```

```
     Pred
Truth        no       yes
  no  0.9458790 0.0541210
  yes 0.5131579 0.4868421
```

total percent correct

```
In [22]: sum(diag(ct))/sum(ct)
```

0.892634372926344
test error is

```
In [23]: round(100*(1-sum(diag(ct))/sum(ct)),2)
```

10.74
not very good, because the 'yes' class is nearly ignored

```
In [24]: (F1 <- harm (prop.table(ct,1)[1,1], prop.table(ct,1)[2,2]))
```

0.642823954390972
Now a random Forest

```
In [25]: library(randomForest)

         model.rf1 <- randomForest(subscribed ~ ., data = learn.data, ntree=100, proximity=FALSE

         model.rf1
```

```
randomForest 4.6-14
Type rfNews() to see new features/changes/bug fixes.



Call:
 randomForest(formula = subscribed ~ ., data = learn.data, ntree = 100,      proximity = FALSE)
               Type of random forest: classification
                     Number of trees: 100
No. of variables tried at each split: 4

        OOB estimate of  error rate: 9.46%
Confusion matrix:
       no  yes class.error
no  25612  988  0.03714286
yes  1864 1677  0.52640497
```

We get an estimated test error (OOB) of 9.3%, so better; let's compute the real test error:

```
In [26]: pred.rf1 <- predict (model.rf1, deposit[test.indexes,], type="class")

         (ct <- table(Truth=deposit$subscribed[test.indexes], Pred=pred.rf1))
```

```
     Pred
Truth    no   yes
  no  12813   509
  yes   913   835
```

percent by class

```
In [27]: prop.table(ct, 1)
```

```
     Pred
Truth         no        yes
  no  0.96179252 0.03820748
  yes 0.52231121 0.47768879
```

total percent correct

```
In [28]: sum(diag(ct))/sum(ct)
```

0.905640345056403
real test error is

```
In [29]: round(100*(1-sum(diag(ct))/sum(ct)),2)
```

9.44
and The F1-score

```
In [30]: (F1 <- harm (prop.table(ct,1)[1,1], prop.table(ct,1)[2,2]))
```

0.638337574357133
So OOB really works in estimating prediction error and the RF is better than a single tree; however, there is a big issue in unbalanced classes
one way to deal with this is to include class weights

```
In [31]: model.rf2 <- randomForest(subscribed ~ .,
                                   data = learn.data,
                                   ntree=100,
                                   proximity=FALSE,
                                   classwt=c(1,10))

         model.rf2
```

```
Call:
 randomForest(formula = subscribed ~ ., data = learn.data, ntree = 100,      proximity = FALSE,
               Type of random forest: classification
                     Number of trees: 100
No. of variables tried at each split: 4

        OOB estimate of  error rate: 9.81%
Confusion matrix:
       no  yes class.error
no  25727  873  0.03281955
yes  2084 1457  0.58853431
```

which helps a little bit, but not much: we get estimated test error (OOB) of 9.86% with a better balance; let's compute the real test error:

```
In [32]: pred.rf2 <- predict (model.rf2,
                              deposit[test.indexes,],
                              type="class")

         (ct <- table(Truth=deposit$subscribed[test.indexes],
                      Pred=pred.rf2))
```

```
     Pred
Truth    no   yes
  no  12885   437
  yes  1030   718
```

percent by class

```
In [33]: prop.table(ct, 1)
```

```
     Pred
Truth         no        yes
  no  0.96719712 0.03280288
  yes 0.58924485 0.41075515
```

total percent correct

```
In [34]: sum(diag(ct))/sum(ct)
```

0.902654280026543
real test error is

```
In [35]: round(100*(1-sum(diag(ct))/sum(ct)),2)
```

9.73
and the F1-score

```
In [36]: (F1 <- harm (prop.table(ct,1)[1,1], prop.table(ct,1)[2,2]))
```

0.57662548348027
another way is to stratify the sampling in the boostrap resamples
'yes' is the less represented class, so we upsample it

```
In [37]: n.yes <- table(learn.data$subscribed)["yes"]
         n.no <- table(learn.data$subscribed)["no"]

         model.rf3 <- randomForest(subscribed ~ .,
                                   data = learn.data,
                                   ntree=100,
                                   proximity=FALSE,
                                   sampsize=c(yes=3000, no=3000),
                                   strata=learn.data$subscribed)

         model.rf3
```

```
Call:
 randomForest(formula = subscribed ~ ., data = learn.data, ntree = 100,      proximity = FALSE,
               Type of random forest: classification
                     Number of trees: 100
No. of variables tried at each split: 4

        OOB estimate of  error rate: 14.52%
Confusion matrix:
       no  yes class.error
no  22682 3918   0.1472932
yes   459 3082   0.1296244
```

which seems to help much more: we get estimated test error (OOB) of 14.4% with a very good balance let's compute the real test error:

```
In [38]: pred.rf3 <- predict (model.rf3, deposit[test.indexes,], type="class")

         (ct <- table(Truth=deposit$subscribed[test.indexes], Pred=pred.rf3))
```

```
     Pred
Truth    no   yes
  no  11347  1975
  yes   217  1531
```

percent by class

```
In [39]: prop.table(ct, 1)
```

```
     Pred
Truth        no       yes
  no   0.8517490 0.1482510
  yes  0.1241419 0.8758581
```

total percent correct

```
In [40]: sum(diag(ct))/sum(ct)
```

0.854545454545454
real test error is

```
In [41]: round(100*(1-sum(diag(ct))/sum(ct)),2)
```

14.55
and F1-score

```
In [42]: (F1 <- harm (prop.table(ct,1)[1,1],
                      prop.table(ct,1)[2,2]))
```

0.863635330951826
Now we can try to optimize the number of trees, guided by OOB:

```
In [43]: (ntrees <- round(10^seq(1,3,by=0.2)))
```

1. 10 2. 16 3. 25 4. 40 5. 63 6. 100 7. 158 8. 251 9. 398 10. 631 11. 1000
prepare the structure to store the partial results

```
In [44]: rf.results <- matrix (rep(0,2*length(ntrees)),
                               nrow=length(ntrees))
         colnames (rf.results) <- c("ntrees", "OOB")
         rf.results[,"ntrees"] <- ntrees
         rf.results[,"OOB"] <- 0

         ii <- 1

         for (nt in ntrees)
         {
           print(nt)

           model.rf <- randomForest(subscribed ~ .,
                                    data = learn.data,
                                    ntree=nt,
                                    proximity=FALSE,
                                    sampsize=c(yes=3000, no=3000),
                                    strata=learn.data$subscribed)
```

```
        # get the OOB
        rf.results[ii,"OOB"] <- model.rf$err.rate[nt,1]

        ii <- ii+1
      }
```

```
[1] 10
[1] 16
[1] 25
[1] 40
[1] 63
[1] 100
[1] 158
[1] 251
[1] 398
[1] 631
[1] 1000
```

In [45]:
```
rf.results
```

ntrees	OOB
10	0.1561618
16	0.1483743
25	0.1507913
40	0.1444212
63	0.1442885
100	0.1452175
158	0.1441558
251	0.1435586
398	0.1443880
631	0.1445208
1000	0.1449852

choose best value of 'ntrees'

In [46]:
```
lowest.OOB.error <- as.integer(which.min(rf.results[,"OOB"]))
(ntrees.best <- rf.results[lowest.OOB.error,"ntrees"])
```

ntrees: 251

we could also try to optimize the number of variables in the same way, though the default values work quite well in general

Now refit the RF with the best value of 'ntrees'

In [47]:
```
model.rf <- randomForest(subscribed ~ .,
                         data = learn.data,
                         ntree=ntrees.best,
                         proximity=FALSE,
                         sampsize=c(yes=3000, no=3000),
                         strata=learn.data$subscribed)
```

let's compute the real test error:

```
In [48]: pred.rf.final <- predict (model.rf,
                                    deposit[test.indexes,],
                                    type="class")

         (ct <- table(Truth=deposit$subscribed[test.indexes],
                      Pred=pred.rf.final))
```

```
     Pred
Truth    no   yes
  no  11354  1968
  yes   206  1542
```

percent by class

```
In [49]: prop.table(ct, 1)
```

```
     Pred
Truth        no       yes
  no  0.8522744 0.1477256
  yes 0.1178490 0.8821510
```

total percent correct

```
In [50]: sum(diag(ct))/sum(ct)
```

0.855739880557399
real test error is

```
In [51]: round(100*(1-sum(diag(ct))/sum(ct)),2)
```

14.43
and the F1-score

```
In [52]: (F1 <- harm (prop.table(ct,1)[1,1], prop.table(ct,1)[2,2]))
```

0.866955409692999
And this is the final model

```
In [53]: print(model.rf)
```

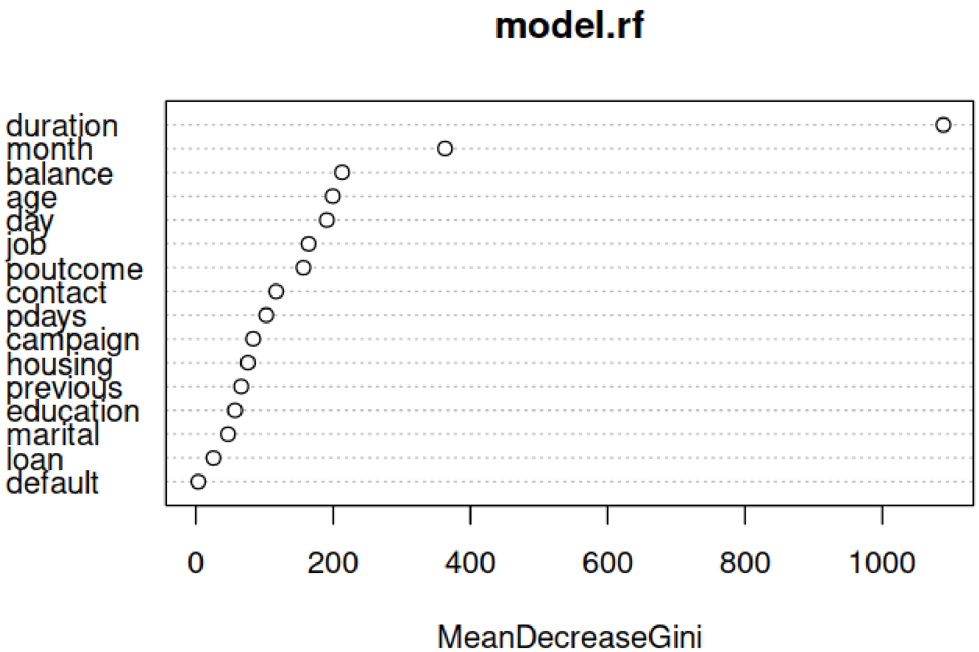
```
Call:
 randomForest(formula = subscribed ~ ., data = learn.data, ntree = ntrees.best,      proximity =
               Type of random forest: classification
                     Number of trees: 251
No. of variables tried at each split: 4
```

```
        OOB estimate of  error rate: 14.39%
Confusion matrix:
       no  yes class.error
no  22708 3892   0.1463158
yes   445 3096   0.1256707
```

The importance of variables

In [54]:
```
importance(model.rf)
options(repr.plot.width=6, repr.plot.height=4)
varImpPlot(model.rf)
```

	MeanDecreaseGini
age	199.57025
job	164.54935
marital	46.93062
education	57.05297
default	3.43785
balance	213.05313
housing	75.90687
loan	25.63931
contact	116.96853
day	190.73564
month	363.12813
duration	1089.08848
campaign	83.62327
pdays	102.66704
previous	66.19663
poutcome	156.71577

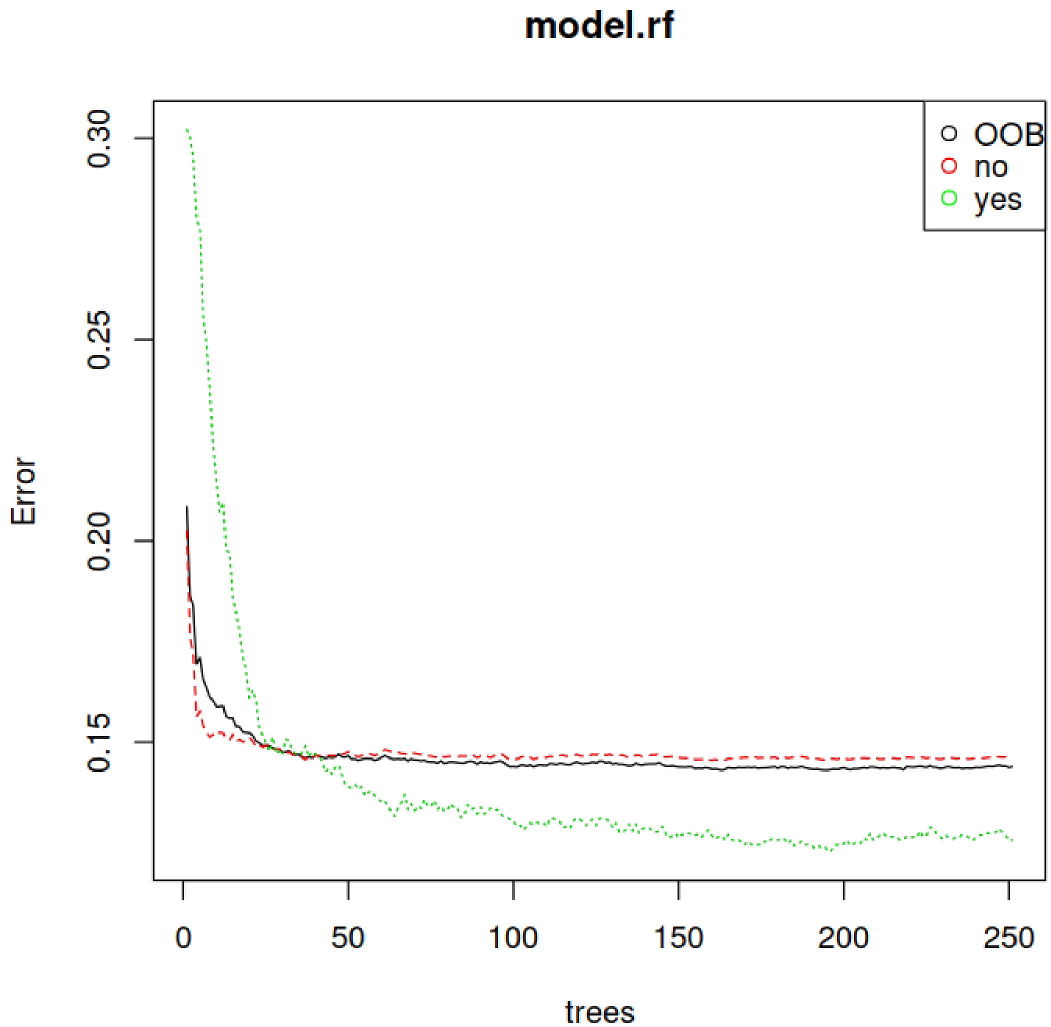


'duration' is the most important variable, then month, etc

plot error rate: black = out of bag (OOB), red = label 1 ('no'), green = label 2 ('yes') as a function of the number of trees used

In [55]:
```
options(repr.plot.width=6, repr.plot.height=6)
plot(model.rf)

legend("topright", legend=c("OOB", "no", "yes"),
       pch=c(1,1), col=c("black","red","green"))
```



What variables are being used in the forest (their counts)

```
In [56]: varUsed(model.rf, by.tree=FALSE,count = TRUE)
```

1. 28586 2. 20921 3. 8893 4. 11181 5. 775 6. 31606 7. 4472 8. 4179 9. 4772 10. 27592 11. 19392 12. 35243 13. 16017 14. 8860 15. 5939 16. 3651