

Introduction to Random Forest



Random Forest

- better performance
- sample subset of the features
- improved version of bagging
- reduced correlation between the sampled trees

R Documentation



Random Forest in R

- > library(randomForest)
- > ?randomForest

randomForest {randomForest}

Classification and Regression with Random Forest

Description

randomForest implements Breiman's random forest algorithm (based on Breiman and Cutler's original Fortran code) for classification and regression. It can also be used in unsupervised mode for assessing proximities among data points.

Usage

```
## S3 method for class 'formula'
randomForest(formula, data=NULL, ..., subset, na.action=na.fail)
## Default S3 method:
randomForest(x, y=NULL, xtest=NULL, ytest=NULL, ntree=500,
             mtry=if (!is.null(y) && !is.factor(y))
             max(floor(ncol(x)/3), 1) else floor(sqrt(ncol(x))),
             replace=TRUE, classwt=NULL, cutoff, strata,
             sampsize = if (replace) nrow(x) else ceiling(.632*nrow(x)),
             nodesize = if (!is.null(y) && !is.factor(y)) 5 else 1,
             maxnodes = NULL,
             importance=FALSE, localImp=FALSE, nPerm=1,
             proximity, oob.prox=proximity,
             norm.votes=TRUE, do.trace=FALSE,
             keep.forest=!is.null(y) && is.null(xtest), corr.bias=FALSE,
             keep.inbag=FALSE, ...)
## S3 method for class 'randomForest'
print(x, ...)
```



randomForest Example

```
library(randomForest)
# Train a default RF model (500 trees)
model <- randomForest(formula = response ~ ., data = train)</pre>
```





Understanding the Random Forest model output



Random Forest output

```
# Print the credit model output
> print(credit model)
Call:
 randomForest(formula = default ~ ., data = credit_train)
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 4
        00B estimate of error rate: 24.12%
Confusion matrix:
     no yes class.error
no 516 46 0.08185053
yes 147 91 0.61764706
```



Out-of-bag error matrix

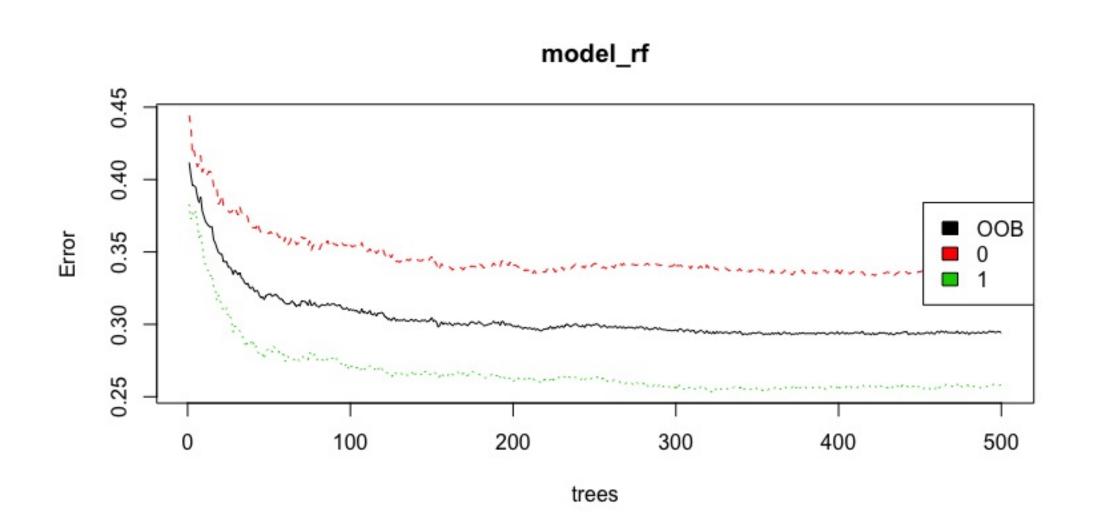


Out-of-bag error estimate

```
# Look at final 00B error rate (last row in err matrix)
> oob err <- err[nrow(err), "00B"]</pre>
> print(oob err)
   00B
0.24125
> print(credit model)
Call:
 randomForest(formula = default ~ ., data = credit train)
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 4
        00B estimate of error rate: 24.12%
Confusion matrix:
     no yes class.error
no 516 46 0.08185053
yes 147 91 0.61764706
```



Plot the OOB error rates







OOB error vs. test set error



Advantages & Disadvantages of OOB estimates

- Can evaluate your model without a separate test set
- ✓ Computed automatically by the randomForest() function
- **★** OOB Error only estimates error (not AUC, log-loss, etc.)
- **★** Can't compare Random Forest performace to other types of models





Tuning a Random Forest model

Random Forest Hyperparameters

- ntree: number of trees
- mtry: number of variables randomly sampled as candidates at each split
- sampsize: number of samples to train on
- nodesize: minimum size (number of samples) of the terminal nodes
- maxnodes: maximum number of terminal nodes



Tuning mtry with tuneRF()

Results table:

```
mtry 00BError
2.00B 2 0.2475
4.00B 4 0.2475
8.00B 8 0.2425
```

