Bagging

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In this lesson we'll learn the how to implement Bagging in R.

Additional packages needed

To run the code you may need additional packages.

- If necessary install the followings packages.

```
install.packages('randomForest');
install.packages('caret');
install.packages('rpart');
install.packages('adabag');
install.packages('ipred');
```

```
library(randomForest)

## randomForest 4.6-12

## Type rfNews() to see new features/changes/bug fixes.

library(caret)

## Loading required package: lattice

## Loading required package: ggplot2

##
## Attaching package: 'ggplot2'

## The following object is masked from 'package:randomForest':
##
##     margin

library(rpart)
library(adabag)

## Loading required package: mlbench

library(ipred)

##
## Attaching package: 'ipred'

## The following object is masked from 'package:adabag':
##
##     bagging
```

Data

We will be using the UCI Machine Learning Repository: Adult Data to predict whether income exceeds $50K/yr based on census data. Also known as "Census Income" dataset.

```
data_url <-
'http://nikbearbrown.com/YouTube/MachineLearning/M09/adult.data.txt'
# Adult data set from UCI
adult<- read.csv(url(data_url), header=FALSE)
head(adult)

##   V1                V2     V3         V4 V5                  V6
## 1 39         State-gov  77516  Bachelors 13       Never-married
## 2 50  Self-emp-not-inc  83311  Bachelors 13  Married-civ-spouse
## 3 38           Private 215646    HS-grad  9            Divorced
## 4 53           Private 234721       11th  7  Married-civ-spouse
## 5 28           Private 338409  Bachelors 13  Married-civ-spouse
## 6 37           Private 284582    Masters 14  Married-civ-spouse
##                   V7             V8     V9     V10  V11 V12 V13
## 1       Adm-clerical  Not-in-family  White    Male 2174   0  40
## 2    Exec-managerial        Husband  White    Male    0   0  13
## 3  Handlers-cleaners  Not-in-family  White    Male    0   0  40
## 4  Handlers-cleaners        Husband  Black    Male    0   0  40
## 5     Prof-specialty           Wife  Black  Female    0   0  40
## 6    Exec-managerial           Wife  White  Female    0   0  40
##              V14    V15
## 1  United-States  <=50K
## 2  United-States  <=50K
## 3  United-States  <=50K
## 4  United-States  <=50K
## 5           Cuba  <=50K
## 6  United-States  <=50K

names(adult)

##  [1] "V1"  "V2"  "V3"  "V4"  "V5"  "V6"  "V7"  "V8"  "V9"  "V10"
"V11"
## [12] "V12" "V13" "V14" "V15"

adult.len <- sample(1:nrow(adult), 3*nrow(adult)/4)
head(adult.len)

## [1]  8718 21045 17531 13301 28165  8835

train <- adult[adult.len,]
test <- adult[-adult.len,]
head(train)

##       V1             V2     V3          V4 V5                  V6
## 8718  64      State-gov 114650         9th  5  Married-civ-spouse
```

```
## 21045 60  Self-emp-inc 181196  Some-college 10  Married-civ-spouse
## 17531 38       Private 220783       HS-grad  9            Divorced
## 13301 37       Private 240810    Assoc-acdm 12  Married-civ-spouse
## 28165 55             ? 141807       HS-grad  9       Never-married
## 8835  23     Local-gov 144165     Bachelors 13       Never-married
##                      V7             V8                  V9     V10
V11
## 8718      Craft-repair        Husband               White    Male
0
## 21045  Exec-managerial        Husband               White    Male
0
## 17531    Other-service  Not-in-family               White  Female
0
## 13301     Craft-repair        Husband               White    Male
0
## 28165                ?  Not-in-family               White    Male
13550
## 8835    Prof-specialty      Own-child  Amer-Indian-Eskimo    Male
0
##       V12 V13            V14    V15
## 8718    0  40  United-States  <=50K
## 21045   0  40  United-States   >50K
## 17531   0  20  United-States  <=50K
## 13301   0  45  United-States  <=50K
## 28165   0  40  United-States   >50K
## 8835    0  30  United-States  <=50K
```

```
head(test)
```

```
##    V1                 V2     V3          V4 V5                  V6
## 2  50  Self-emp-not-inc  83311  Bachelors 13  Married-civ-spouse
## 8  52  Self-emp-not-inc 209642    HS-grad  9  Married-civ-spouse
## 20 43  Self-emp-not-inc 292175    Masters 14            Divorced
## 24 43           Private 117037       11th  7  Married-civ-spouse
## 25 59           Private 109015    HS-grad  9            Divorced
## 29 39           Private 367260    HS-grad  9            Divorced
##                    V7             V8     V9     V10 V11  V12 V13
## 2    Exec-managerial        Husband  White    Male   0    0  13
## 8    Exec-managerial        Husband  White    Male   0    0  45
## 20   Exec-managerial      Unmarried  White  Female   0    0  45
## 24  Transport-moving        Husband  White    Male   0 2042  40
## 25      Tech-support      Unmarried  White  Female   0    0  40
## 29   Exec-managerial  Not-in-family  White    Male   0    0  80
##                V14    V15
## 2   United-States  <=50K
## 8   United-States   >50K
## 20  United-States   >50K
## 24  United-States  <=50K
## 25  United-States  <=50K
## 29  United-States  <=50K
```

Bootstrap aggregating (bagging)

Create ensembles by bootstrap aggregation, i.e., repeatedly randomly re-sampling training data. Not that bagging uses the same learner so bias related to the method isn't addressed by this approach.

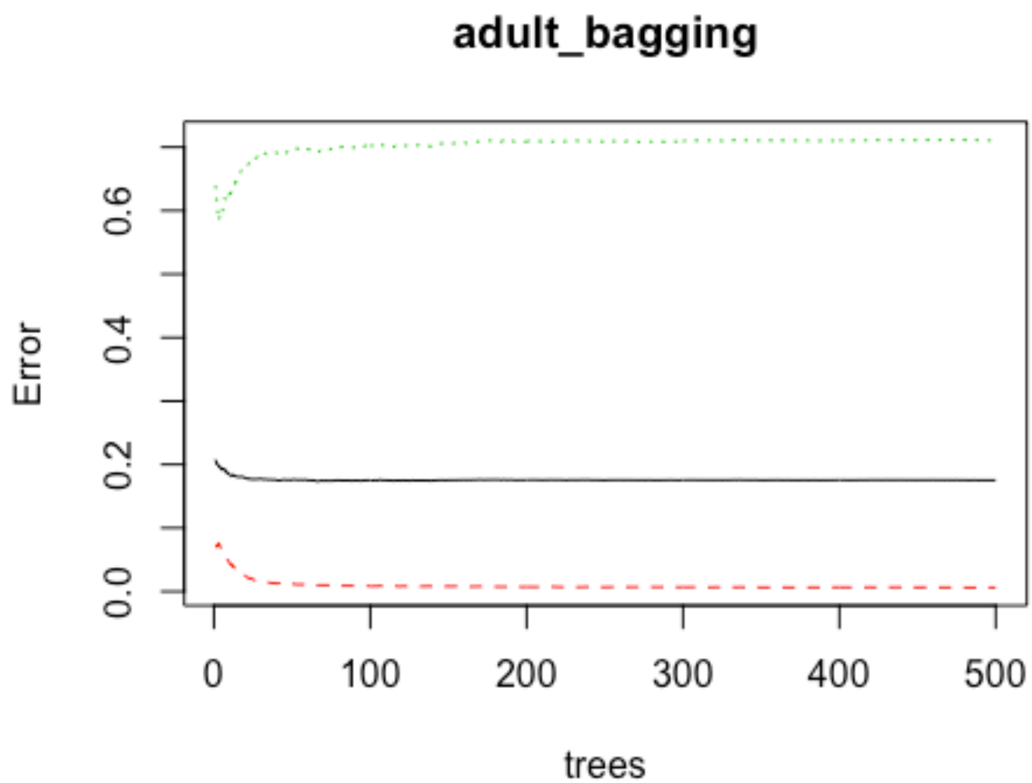
Bootstrap: draw n items from X with replacement

Bootstrap aggregating: combines random learners (often with voting, averaging or median) to create a predictor lesss efected by noise. Unstable and/or noisy algorithms often profit from bagging.

Bagging's usefulness depends on the stability of the base classifiers. If small changes in the sample cause small changes in the base-level classifier, then the ensemble will not be much better than the base classifiers. It reduces variance and helps to avoid overfitting. It is often applied to decision tree methods (random forests) and nearest neighbor classifiers, but it can be used with any type of method.

Bagging in R

```
adult_bagging <- randomForest(V15~.,data=adult, subset=adult.len,
mtry=14, importance=TRUE)
plot(adult_bagging)
```




```
adult_predict <- predict(adult_bagging, test)
adult_predict_confusion <- confusionMatrix(adult_predict, test$V15)
adult_predict_confusion$table

##             Reference
## Prediction  <=50K  >50K
##      <=50K   6120  1406
##      >50K      40   575

accuracy <- adult_predict_confusion$overall[1]
accuracy

##  Accuracy
## 0.8223805

# importance of predictors
adult_bagging$importance

##              <=50K          >50K MeanDecreaseAccuracy
MeanDecreaseGini
## V1   0.0049306561  0.0144419426         0.0072111415
1085.84109
## V2   0.0024906046  0.0054135851         0.0031887608
286.75055
```

```
## V3  -0.0001988956 -0.0005500772        -0.0002857537
1626.98627
## V4   0.0137654219 -0.0097888796         0.0081132433
143.84481
## V5   0.0203861588 -0.0029534161         0.0147879156
998.69198
## V6   0.0355076407 -0.0040624276         0.0260138458
73.45320
## V7   0.0094921128  0.0181764887         0.0115749347
636.33629
## V8   0.0429096933 -0.0031834822         0.0318485641
1825.19284
## V9   0.0003204685  0.0001255798         0.0002739902
85.63695
## V10  0.0030428349 -0.0012649488         0.0020088294
48.08797
## V11  0.0363483998  0.1129306290         0.0547238671
964.89803
## V12  0.0053528498  0.0420863700         0.0141673485
303.82477
## V13  0.0050087254  0.0041056740         0.0047908228
623.62269
## V14 -0.0002026956 -0.0001912583        -0.0001998350
207.64357
```

```
# ipred package
adult_bagging <- ipredbagg(train$V15, X=train[,-15], nbagg=25,
                           control=rpart.control(minsplit=2, cp=0,
xval=0),
                           comb=NULL, coob=FALSE, ns=length(train$V15),
keepX = TRUE)
adult_predict <- predict(adult_bagging, test)
adult_predict_confusion <- confusionMatrix(adult_predict, test$V15)
adult_predict_confusion$table
```

```
##             Reference
## Prediction  <=50K  >50K
##      <=50K   5694   748
##      >50K     466  1233
```

```
accuracy <- adult_predict_confusion$overall[1]
accuracy
```

```
##  Accuracy
## 0.8508783
```

Resources

- [Improve Predictive Performance in R with Bagging via @rbloggers](http://www.r-bloggers.com/improve-predictive-performance-in-r-with-bagging/)
- bagging {adabag} | inside-R | A Community Site for R
- bagging {ipred} | inside-R | A Community Site for R
- Bagging / Bootstrap Aggregation with R