What and When of Random Forest

Debpriya Seal
,School of Informatics and Computing
Indiana University
Bloomington, Indiana 47405-7000
Email: debseal@indiana.edu

***Abstract*—Random Forest has been in highlight lately. Argueably it is best classifiction algorithm we have. This paper provides a light introduction to Random forest. This paper starts with the basics, and then will show to application of the same in R with a toy example.**

***Index Terms*—Random Forest, Bootstrap Aggregation/Bagging, R, Python**

I. Introduction

A. For a layman

RANDOM Forest is a learning method to classify or predict the values of objects. However, it is a bit different from the usual methods which predicts or classify objects. In general, there is this one classifier which classifies/predicts objects. However, in random forest we make bunch of them, and try to keep them as different as possible by imputing randomness. And the classifier we use are decision trees. Hence, random + forest i.e random forest.

B. Formally

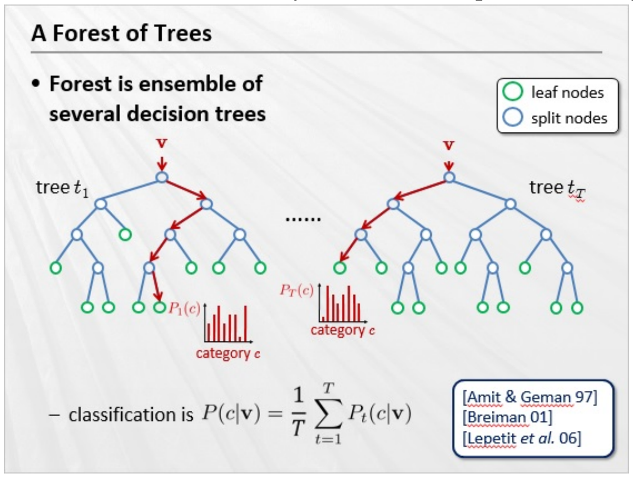
RANDOM forest is ensemble learning method used for classification (or regression). There are 2 terms we need to know before we go any further with Random forest is Decision trees and ensemble Methods. Let first understand them briefly.

1) Decision trees: Decision Trees is a classifcation algorithm. Later on, you will see that Random forest is nothing but a bunch of decision trees put together.Decision tree, the name has it. It is an algorithm in which we create a tree to classify objects. An input enters enter the top of the tree and as it traverse down the tree, the input data gets bucketed into smaller and smaller sets, to reach a leaf node which predicts the class/category it belongs to.

2) Ensemble Methods: This is method to improve the classification accuracy. It uses the divide-and-conquer approach. The basic idea is that a group of " weak learners" come together to form a "strong learner". And the way this is achieved is by building bunch of classifier, and then using the prediction from each of them together to come up with the final prediction. The idea is simple, that one classifier may go wrong, 2 may go wrong, but not all of them can go wrong. And we classfiy a test object to be the one which is the majority of all. Now you can create ensemble of classfiers in many way:

Prof. M Dailklic with Indiana University for consistent support and encouragement

1) **Using Training datasets**: In this method we resample from the given training set based on some sampling distribution. Boosting and Bagging are the example of ensemble methods which uses training datasets.
2) **Using Input Features**: In this we rather using different trainings records, we use different subset of features to train different classifiers.
3) **Using Class Labels**: This method is used when you tons of class labels. You divide the labels into 2 binary class. And then train on these two labels. You perform this recursively.
4) **Using learning algortihm**: There are learning algorithms in which you can tweak the algortihm to has classifiers react different. Typical example would be that of NN (Neural Network). By changing the weights attached to each link, you can get a classfier behave different. Similarly, with decision trees, instead of choosing the best feature, choose randomly between the top i^th randomly



Now, Random forest is an amalgamation of the above 2 ideas (i.e. Decision Trees and Ensemble methods). We make bunch of Decision trees(our weak learner).And then we get the prediction from each of the decision trees. And now maybe the forest starts to make more sense. And the Random forest is the strong leaner, which predicts the class which majority of the decision trees predicted.However, it should not be difficult ot see that you want these individual trees (decision trees) to as different as possible. Since, if they are identical, then there is no difference between your tree and random forest. The term random refers to the randomness you would like to keep in these individual decision trees.
Now, you would be thinking what is this randomness we are talking about in the random forest. So, there are 2 type of

randomness we incorporate in Random Forest:

a. **Boostrap Aggregation(or Bagging)**: *Boostrap Aggregation(or Bagging)* is a ensemble technique in which we repeatedly re-sample (say N times) with replacement, according to some unfiorm probability distribution. We this to pick different set of training dataset for each classifer C_k.
b. **Random subspace**: Once we get the training dataset D_k. At each node, we know randomly pick say f subset features from the set of feature F. And then based on some measure (entropy, genie etc.) we pick the best feautre from these f subset of feature and not complete F set of features. Small number of f, may decrease you chances of trees being correlated .On the other hand, big number of features gives your tree more strenght. So as a thumb rule $f = \log_2 F + 1$ where F is the total number of features.

Also to measure the error of random forest, below equation is used:

$$GeneralizationError \leq \frac{\bar{\rho}(1-s^2)}{s^2} \quad (1)$$

where $\bar{\rho}$ is the average correlation between the different trees and s is the strength of the tree.The above equation is pretty much straightforward. You would not want to have an correlation between any of your individual trees. If you have more identical trees then the bound of the generalization error tends to increase. Below is a pseudo-code for the Random Forest:

Algorithm Random Forest

```
1: Let D be $\{(x_1, y_1),(x_2, y_2),(x_3, y_3), \dots,(x_n, y_n)\}$
2: Let $x_i \in \mathbb{R}^F$ i.e. $x_i = \{a_1, a_2, a_3, \dots, a_F\}$
3: Let $c$ be the number so classifiers we intend to make
4: for $i = 1 \dots c$ do
5:     Choose a bootstrap sample $D_i$ from D
6:     Train a classifier on $D_i$ dataset such that:
7:         a) You do not prune the tree, and let grow fully.
8:         b) For each node, randomly pick f subset features of
9:         features i.e. $f < F$
10: end for
11: for each test data i do
12:     Test it on all $c$ classifier and pick majority
13:     votes for classifcation (or average for regression)
14: end for
```

II. Toy Example To Illustrate

Lets try to understand the concept with a toy example. Lets take an example in which we are trying to predict wether a person has fever or not based on 3 sypmtoms. Lets see how random forest will work on this.

Step 1: Sample N records (say 2) from the above dataset (with replacement).

Step 2: Assuming we are making forest of 2 decision trees. For the first tree we sampled records 1 and 2. Clearly we can see that it will have root and leaf node straight away. As for both of it cases, we have the class to be N.
Similarly, suppose we pick records 3,4 and 5 for the second tree and here as well everything is Y. So again we get the same tree.

Step 3: Given a test record we ask all the above tree and we take the majority. So this is how classification works in Random Forest.

TABLE I: Dataset for Classification

S.No.	Fever	Nausea	Weakness	Viral
1	0	0	Mild	N
2	0	1	High	N
3	1	0	Low	Y
4	1	1	Mild	Y
5	1	0	High	N
6	1	1	High	Y

III. Application in R

R already has a inbuild package to implement Random forest. And as the first step you would like to install the same. Below is how you can do so:

```
> install.packages("randomForest")
```

Once you have the library installed, you should load the package.And below is how you do that.

```
> library("randomForest")
```

NOTE: You could also require(”randomForest”). The only difference being, library() throws an error if the library is not found. However, require() does not, hence require is generally used in functions more often.

The next thing is to get some kind of dataset to train/test random Forest. We will use the *iris* dataset, which comes in default with almost all R installations. So the only thing you need to do is load the dataset. Below is how you can do so:

```
> load(iris)
```

Now lets create training adn test dataset out of it.

```
> train = sample (1:nrow(iris),nrow(iris)/2)
> test = iris[ c(1:100), ]
```

And now we call the real function i.e. *randomForest*. Below is how we call it.

```
> iris.train = randomForest(Species ~., data=train
importance=TRUE, do.trace=100)
```

Lets discuss the arguments of randomForest:

1) *data* : Here you mention the dataset you want to be used for training.
2) *importance* : It takes a boolean value, were you mention that you would like to assess the importance of feature.
3) *do.trace* : It is to set the verbose mode on/off.
4) *mtry* : In random forest the number of features selected is a factor. And you decide that using this argument. By default, for regression this is $p/3$ and for classification $\sqrt{p}$. For details on all parameter please look at http://lojze.lugos.si/~darja/software/r/library/randomForest/html/randomForest.html

Now we lets see what does randomForest function return. For that we execute below command or just iris.train.

```
> print(iris.train)
Call:
 randomForest(formula = Species ~ .,
data = iris, mtry = 3, importance = TRUE,
do.trace = 100, subset = train)

Type of random forest: classification
Number of trees: 500
No. of variables tried at each split: 3

OOB estimate of  error rate: 5.33%
Confusion matrix:
           setosa versicolor virginica
setosa         25          0         0
versicolor      0         23         2
virginica       0          2        23
                class.error
setosa         0.00
versicolor     0.08
virginica      0.08
```

At last its time to predict and we execute the below command to achieve the same: (For deatils on predict http://hosho.ees.hokudai.ac.jp/~kubo/Rdoc/library/randomForest/html/predict.randomForest.html)

```
> iris.predict = predict(iris.train, test)
```

And now its time to see the output.

```
> iris.predict
        11          12          13          14
    setosa      setosa      setosa      setosa
        18          19          20          21
    setosa      setosa      setosa      setosa
        25          26          27          28
    setosa      setosa      setosa      setosa
        32          33          34          35
    setosa      setosa      setosa      setosa
        39          40          41          42
    setosa      setosa      setosa      setosa
        46          47          48          49
    setosa      setosa      setosa      setosa
        63          64          65          66
versicolor versicolor versicolor versicolor
        70          71          72          73
versicolor versicolor versicolor versicolor
        77          78          79          80
versicolor  virginica versicolor versicolor
        84          85          86          87
versicolor versicolor versicolor versicolor
        91          92          93          94
versicolor versicolor versicolor versicolor
        98          99         100
versicolor versicolor versicolor
Levels: setosa versicolor virginica
```

A better way would be.

```
> confMat = table(observed=test[,'Species'],
iris.predict)
> confMat
             iris.predict
observed     setosa versicolor virginica
  setosa         40          0         0
  versicolor      0         39         1
  virginica       0          0         0
```

And with this we are finally done

IV. Pros & Cons

A. Pros

- More robust to noise.
- Running time is not huge and have a high accuracy.
- Can handle huge input features.
- Adapt to Class imbalance problem.

B. Cons

- May fall prey to overfitting.

V. Conclusion

To conclude, Random forest is the best classification algorithm right now. And its a necessary skill to have in your arsenal. Especially when you are dealing with data analysis.

Acknowledgment

I would like to thank Prof. M. Daiklic, for constant supervision and motivation to understand the problem in details.

References

[1] Pang-Ning Tan, Vipin Kumar and Michael Steinbach, *Intorduction to Data Mining*, 12th impression : Pearson, 2006.
[2] *A Gentle Introduction to Random Forests, Ensembles, and Performance Metrics in a Commercial System* http://citizennet.com/blog/2012/11/10/random-forests-ensembles-and-performance-metrics/
[3] *Computational Prediction* http://mkseo.pe.kr/stats/?p=220
[4] Gareth James, Daniela Witten, Trevor Hastie and Robert Tibshirani, *Introduction to Statistical Learning - with Application in R*, : Springer, 2013.

Debpriya Seal He is graudate student in his 2nd year, pursuing his M.S. in Computer Science. His interest lies in Data Mining and predictive modelling. He has 5 years of Datawarehousing experience with Accenture under his belt. He is in IU Bloomington 9-ball pool team.