xgboost Package Example (Version 0.3-0)

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1 Introduction

This is an introductory document of using the xgboost package in R. xgboost is short for eXtreme Gradient Boosting (Tree). It is an efficient and scalable implementation of Friedman et al. (2001). It supports regression and classification analysis on different types of input datasets.

It has several features:

- 1. Speed: xgboost can automatically do parallel computation on Windows and Linux, with openmp. It is generally over 10 times faster than gbm.
- 2. Input Type: xgboost takes several types of input data:
 - Dense Matrix: R's dense matrix, i.e. matrix
 - Sparse Matrix: R's sparse matrix Matrix::dgCMatrix
 - Data File: Local data files
 - xgb.DMatrix: xgboost's own class. Recommended.
- 3. Sparsity: xgboost accepts sparse input for both tree booster and linear booster.
- 4. Customization: xgboost supports customized objective function and evaluation function
- Performance: xgboost has better performance on several different datasets.
 Its rising popularity and fame in different Kaggle competitions is the evidence.

2 Example with iris

In this section, we will illustrate some common usage of xgboost.

xgboost is the main function to train a Booster, i.e. a model. predict does prediction on the model.

Here we can save the model to a binary local file, and load it when needed. We can't inspect the trees inside. However we have another function to save the model in plain text.

It is important to know xgboost's own data type: xgb.DMatrix. It speeds up xgboost.

We can use xgb.DMatrix to construct an xgb.DMatrix object:

```
> iris.mat <- as.matrix(iris[,1:4])
> iris.label <- as.numeric(iris[,5])
> diris <- xgb.DMatrix(iris.mat, label = iris.label)
> class(diris)
[1] "xgb.DMatrix"
```

3 Advanced Examples

The function **xgboost** is a simple function with less parameters, in order to be R-friendly. The core training function is wrapped in **xgb.train**. It is more flexible than **xgboost**, but it requires users to read the document a bit more carefully.

xgb.train only accept a xgb.DMatrix object as its input, while it supports some additional features as custom objective and evaluation functions.

```
> logregobj <- function(preds, dtrain) {</pre>
     labels <- getinfo(dtrain, "label")</pre>
     preds <- 1/(1 + exp(-preds))
     grad <- preds - labels
     hess <- preds * (1 - preds)
     return(list(grad = grad, hess = hess))
+ }
> evalerror <- function(preds, dtrain) {
    labels <- getinfo(dtrain, "label")</pre>
    err <- sqrt(mean((preds-labels)^2))</pre>
    return(list(metric = "MSE", value = err))
+ }
> dtest <- slice(diris,1:100)</pre>
> watchlist <- list(eval = dtest, train = diris)
> param <- list(max_depth = 2, eta = 1, silent = 1)
> bst <- xgb.train(param, diris, nround = 2, watchlist, logregobj, evalerror)
[1]
           eval-MSE:3.264351
                                      train-MSE:4.559875
[2]
           eval-MSE:58.79757
                                      train-MSE:66.24299
```

The gradient and second order gradient is required for the output of customized objective function.

We also have slice for row extraction. It is useful in cross-validation.

For a walkthrough demo, please see R-package/demo/demo.R for further details.

4 The Higgs Boson competition

We have made a demo for the Higgs Boson Machine Learning Challenge. Here are the instructions to make a submission

- 1. Download the datasets and extract them to data/.
- 2. Run scripts under xgboost/demo/kaggle-higgs/: higgs-train.R and higgs-pred.R. The computation will take less than a minute on Intel i7.
- 3. Go to the submission page and submit your result.

We provide a script to compare the time cost on the higgs dataset with gbm and xgboost. The training set contains 350000 records and 30 features.

xgboost can automatically do parallel computation. On a machine with Intel i7-4700MQ and 24GB memories, we found that xgboost costs about 35 seconds, which is about 20 times faster than gbm. When we limited xgboost to use only one thread, it was still about two times faster than gbm.

Meanwhile, the result from xgboost reaches 3.60@AMS with a single model. This results stands in the top 30% of the competition.

References

Friedman, Jerome H. (2001). Greedy function approximation: a gradient boosting machine. In *Annals of Statistics* (2001): 1189-1232.

Friedman, Jerome, Trevor Hastie, and Robert Tibshirani. (2000). Additive logistic regression: a statistical view of boosting (with discussion and a rejoinder by the authors). *The annals of statistics* 28.2 (2000):337-407.