Package ‘irboost’

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Title Iteratively Reweighted Boosting for Robust Analysis

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Description Fit a predictive model with the iteratively reweighted boosting (IRBoost) that minimizes the robust loss functions in the CC-family (concave-convex). The convex optimization is conducted by functional descent boosting algorithm in the R package xgboost. The IRBoost reduces the weight of the observation that leads to a large loss; it also provides weights to help identify outliers. Applications include the robust generalized linear models and extensions, where the mean is related to the predictors by boosting, and robust accelerated failure time models. The package supersedes the R package ccboost. Wang (2021) <arXiv:2101.07718>.

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R topics documented:

`dataLS` *generate random data for classification as in Long and Servedio (2010)*

Description

generate random data for classification as in Long and Servedio (2010)

Usage

```
dataLS(ntr, ntu = ntr, nte, percon)
```

Arguments

`ntr`	number of training data
`ntu`	number of tuning data, default is the same as `ntr`
`nte`	number of test data
`percon`	proportion of contamination, must between 0 and 1. If `percon` > `0`, the labels of the corresponding percenrage of response variable in the training and tuning data are flipped.

Value

a list with elements xtr, xtu, xte, ytr, ytu, yte for predictors of disjoint training, tuning and test data, and response variable -1/1 of training, tuning and test data.

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References

P. Long and R. Servedio (2010), *Random classification noise defeats all convex potential boosters*, *Machine Learning Journal*, 78(3), 287–304.

Examples

```
dat <- dataLS(ntr=100, nte=100, percon=0)
```

`irboost` *fit a robust predictive model with iteratively reweighted boosting algorithm*

Description

Fit a predictive model with the iteratively reweighted convex optimization (IRCO) that minimizes the robust loss functions in the CC-family (concave-convex). The convex optimization is conducted by functional descent boosting algorithm in the R package **xgboost**. The iteratively reweighted boosting (IRBoost) algorithm reduces the weight of the observation that leads to a large loss; it also provides weights to help identify outliers. Applications include the robust generalized linear models and extensions, where the mean is related to the predictors by boosting, and robust accelerated failure time models.

Usage

```
irboost(
  x,
  y,
  weights,
  cfun = "ccave",
  s = 1,
  delta = 0.1,
  dfun = "reg:squarederror",
  iter = 10,
  nrounds = 100,
  del = 1e-10,
  trace = FALSE,
  ...
)
```

Arguments

`x`	input matrix, of dimension nobs x nvars; each row is an observation vector. Can accept `dgCMatrix`
`y`	response variable. Quantitative for `dfun="greg:squarederror"`, `dfun="count:poisson"` (non-negative counts) or `dfun="reg:gamma"` (positive). For `dfun="binary:logitraw"` or `"binary:hinge"`, `y` should be a factor with two levels
`weights`	vector of nobs with non-negative weights
`cfun`	concave component of CC-family, can be `"hacve"`, `"acave"`, `"bcave"`, `"ccave"`, `"dcave"`, `"ecave"`, `"gcave"`, `"hcave"`. See Table 2 in https://arxiv.org/pdf/2010.02848.pdf
`s`	tuning parameter of `cfun`. `s` > `0` and can be equal to 0 for `cfun="tcave"`. If `s` is too close to 0 for `cfun="acave"`, `"bcave"`, `"ccave"`, the calculated weights can become 0 for all observations, thus crash the program
`delta`	a small positive number provided by user only if `cfun="gcave"` and `0` < `s` <1

dfun
: type of convex component in the CC-family, the second C, or convex down, that's where the name dfun comes from. It is the same as objective in the xgboost package.

- reg:squarederror Regression with squared loss.
- binary:logitraw logistic regression for binary classification, predict linear predictor, not probabilies.
- binary:hinge hinge loss for binary classification. This makes predictions of -1 or 1, rather than producing probabilities.
- multi:softprob softmax loss function for multiclass problems. The result contains predicted probabilities of each data point in each class, say p_k, k=0, ..., nclass-1. Note, label is coded as in [0, ..., nclass-1]. The loss function cross-entropy for the i-th observation is computed as -log(p_k) with k=lable_i, i=1, ..., n.
- count:poisson: Poisson regression for count data, predict mean of poisson distribution.
- reg:gamma: gamma regression with log-link, predict mean of gamma distribution. The implementation in xgboost takes a parameterization in the exponential family:
  xgboost/src/src/metric/elementwise_metric.cu.
  In particularly, there is only one parameter psi and set to 1. The implementation of the IRCO algorithm follows this parameterization. See Table 2.1, McCullagh and Nelder, Generalized linear models, Chapman & Hall, 1989, second edition.
- reg:tweedie: Tweedie regression with log-link. See also tweedie_variance_power in range: (1,2). A value close to 2 is like a gamma distribution. A value close to 1 is like a Poisson distribution.

iter
: number of iteration in the IRCO algorithm

nrounds
: boosting iterations within each IRCO iteration

del
: convergency criteria in the IRCO algorithm, no relation to delta

trace
: if TRUE, fitting progress is reported

...
: other arguments passing to xgboost

Value

An object with S3 class xgboost with the additional elments:

- weight_update_log a matrix of nobs row by iter column of observation weights in each iteration of the IRCO algorithm
- weight_update a vector of observation weights in the last IRCO iteration that produces the final model fit
- loss_logsum of loss value of the composite function cfun(dfun) in each IRCO iteration. Note, cfun requires dfun non-negative in some cases. Thus some dfun needs attentions. For instance, with dfun="reg:gamma", the loss value is defined gamma-nloglik - (1+log(min(y))). The second term is introduced such that the loss value is non-negative. In fact, gamma-nloglik=y/ypre + log(ypre) in the xgboost, where ypre is the mean prediction value, can be negative. It can be derived that for fixed y, the minimum value of gamma-nloglik is

achived at ypre=y, or 1+log(y). Thus, among all y values, the minimum of gamma-nloglik is 1+log(min(y)).

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References

Wang, Zhu (2021), *Unified Robust Boosting*, arXiv eprint, https://arxiv.org/abs/2101.07718

Examples

```
# regression, logistic regression, hinge regression, Poisson regression
x <- matrix(rnorm(100*2),100,2)
g2 <- sample(c(0,1),100,replace=TRUE)
fit1 <- irboost(x, g2, cfun="acave",s=0.5, dfun="reg:squarederror", trace=TRUE,
                verbose=0, max.depth=1, nrounds=50)
fit2 <- irboost(x, g2, cfun="acave",s=0.5, dfun="binary:logitraw", trace=TRUE,
                verbose=0, max.depth=1, nrounds=50)
fit3 <- irboost(x, g2, cfun="acave",s=0.5, dfun="binary:hinge", trace=TRUE,
                verbose=0, max.depth=1, nrounds=50)
fit4 <- irboost(x, g2, cfun="acave",s=0.5, dfun="count:poisson", trace=TRUE,
                verbose=0, max.depth=1, nrounds=50)

# Gamma regression
x <- matrix(rnorm(100*2),100,2)
g2 <- sample(rgamma(100, 1))
library("xgboost")
fit5 <- xgboost(x, g2, objective="reg:gamma", max.depth=1, nrounds=50)
fit6 <- irboost(x, g2, cfun="acave",s=5, dfun="reg:gamma", trace=TRUE,
                verbose=0, max.depth=1, nrounds=50)
plot(predict(fit5, x), predict(fit6, x))
hist(fit6$weight_update)
plot(fit6$loss_log)
summary(fit6$weight_update)

# Tweedie regression
fit6t <- irboost(x, g2, cfun="acave",s=5, dfun="reg:tweedie", trace=TRUE,
                verbose=0, max.depth=1, nrounds=50)
# Gamma vs Tweedie regression
hist(fit6$weight_update)
hist(fit6t$weight_update)
plot(predict(fit6, x), predict(fit6t, x))

# multiclass classification in iris dataset:
lb <- as.numeric(iris$Species)-1
num_class <- 3
set.seed(11)
```

```
# xgboost
bst <- xgboost(data=as.matrix(iris[, -5]), label=lb,
max_depth=4, eta=0.5, nthread=2, nrounds=10, subsample=0.5,
objective="multi:softprob", num_class=num_class)
# predict for softmax returns num_class probability numbers per case:
pred <- predict(bst, as.matrix(iris[, -5]))
# reshape it to a num_class-columns matrix
pred <- matrix(pred, ncol=num_class, byrow=TRUE)
# convert the probabilities to softmax labels
pred_labels <- max.col(pred)-1
# classification error
sum(pred_labels!=lb)/length(lb)

# irboost
fit7 <- irboost(x=as.matrix(iris[, -5]), y=lb, cfun="acave", s=50,
                dfun="multi:softprob", trace=TRUE, verbose=0,
                max.depth=4, eta=0.5, nthread=2, nrounds=10,
                subsample=0.5, num_class=num_class)
pred7 <- predict(fit7, as.matrix(iris[, -5]))
pred7 <- matrix(pred7, ncol=num_class, byrow=TRUE)
# convert the probabilities to softmax labels
pred7_labels <- max.col(pred7) - 1
# classification error: 0!
sum(pred7_labels != lb)/length(lb)
table(pred_labels, pred7_labels)
hist(fit6$weight_update)
```

`irboost_aft` *fit a robust accelerated failure time model with iteratively reweighted boosting algorithm*

Description

Fit an accelerated failure time model with the iteratively reweighted convex optimization (IRCO) that minimizes the robust loss functions in the CC-family (concave-convex). The convex optimization is conducted by functional descent boosting algorithm in the R package **xgboost**. The iteratively reweighted boosting (IRBoost) algorithm reduces the weight of the observation that leads to a large loss; it also provides weights to help identify outliers. For time-to-event data, an accelerated failure time model (AFT model) provides an alternative to the commonly used proportional hazards models. Note, `irboost` with `dfun=survival:aft` is the wrapper of `irboost_aft`, which was developed to facilitate a different data input format used in `xgb.train` not in `xgboost` at the time.

Usage

```
irboost_aft(
  params,
  data,
  cfun = "ccave",
```

```
    s = 1,
    delta = 0.1,
    iter = 10,
    nrounds = 100,
    del = 1e-10,
    trace = FALSE,
    ...
)
```

Arguments

params	the list of parameters used in xgb.train of **xgboost**. Must include aft_loss_distribution, aft_loss_distribution_scale, but there is no need to include objective. The complete list of parameters is available in the online documentation.
data	training dataset. irboost_aft accepts only an xgb.DMatrix as the input.
cfun	concave component of CC-family, can be "hacve","acave","bcave","ccave", "dcave","ecave","gcave","hcave". See Table 2 in https://arxiv.org/pdf/2010.02848.pdf
s	tuning parameter of cfun. s > 0 and can be equal to 0 for cfun="tcave". If s is too close to 0 for cfun="acave","bcave","ccave", the calculated weights can become 0 for all observations, thus crash the program
delta	a small positive number provided by user only if cfun="gcave" and 0 < s <1
iter	number of iteration in the IRCO algorithm
nrounds	boosting iterations in xgb.train within each IRCO iteration
del	convergency criteria in the IRCO algorithm, no relation to delta
trace	if TRUE, fitting progress is reported
...	other arguments passing to xgb.train

Value

An object of class xgb.Booster with additional elements:

- weight_update_log a matrix of nobs row by iter column of observation weights in each iteration of the IRCO algorithm
- weight_update a vector of observation weights in the last IRCO iteration that produces the final model fit
- loss_log sum of loss value of the composite function cfun(survival_aft_distribution) in each IRCO iteration

Author(s)

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References

Wang, Zhu (2021), *Unified Robust Boosting*, arXiv eprint, https://arxiv.org/abs/2101.07718

See Also

irboost

Examples

```
library("xgboost")
X <- matrix(1:5, ncol=1)

# Associate ranged labels with the data matrix.
# This example shows each kind of censored labels.
#                   uncensored  right  left  interval
y_lower = c(10,  15, -Inf, 30, 100)
y_upper = c(Inf, Inf,   20, 50, Inf)
dtrain <- xgb.DMatrix(data=X, label_lower_bound=y_lower, label_upper_bound=y_upper)
                 params = list(objective="survival:aft", aft_loss_distribution="normal",
                      aft_loss_distribution_scale=1, max_depth=3, min_child_weight= 0)
watchlist <- list(train = dtrain)
bst <- xgb.train(params, dtrain, nrounds=15, watchlist=watchlist)
predict(bst, dtrain)
bst_cc <- irboost_aft(params, dtrain, nrounds=15, watchlist=watchlist, cfun="hcave",
                      s=1.5, trace=TRUE, verbose=0)
bst_cc$weight_update
predict(bst_cc, dtrain)
```

Index