

# Package ‘xgboost’

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**Type** Package

**Title** Extreme Gradient Boosting

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**Description** Extreme Gradient Boosting, which is an efficient implementation of the gradient boosting framework from Chen & Guestrin (2016) <[doi:10.1145/2939672.2939785](https://doi.org/10.1145/2939672.2939785)>. This package is its R interface. The package includes efficient linear model solver and tree learning algorithms. The package can automatically do parallel computation on a single machine which could be more than 10 times faster than existing gradient boosting packages. It supports various objective functions, including regression, classification and ranking. The package is made to be extensible, so that users are also allowed to define their own objectives easily.

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**URL** <https://github.com/dmlc/xgboost>

**BugReports** <https://github.com/dmlc/xgboost/issues>

**NeedsCompilation** yes

**VignetteBuilder** knitr

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### a-compatibility-note-for-saveRDS-save

*Do not use `saveRDS` or `save` for long-term archival of models. Instead, use `xgb.save` or `xgb.save.raw`.*

---

## Description

It is a common practice to use the built-in `saveRDS` function (or `save`) to persist R objects to the disk. While it is possible to persist `xgb.Booster` objects using `saveRDS`, it is not advisable to do so if the model is to be accessed in the future. If you train a model with the current version of XGBoost and persist it with `saveRDS`, the model is not guaranteed to be accessible in later releases of XGBoost. To ensure that your model can be accessed in future releases of XGBoost, use `xgb.save` or `xgb.save.raw` instead.

## Details

Use `xgb.save` to save the XGBoost model as a stand-alone file. You may opt into the JSON format by specifying the JSON extension. To read the model back, use `xgb.load`.

Use `xgb.save.raw` to save the XGBoost model as a sequence (vector) of raw bytes in a future-proof manner. Future releases of XGBoost will be able to read the raw bytes and re-construct the corresponding model. To read the model back, use `xgb.load.raw`. The `xgb.save.raw` function is useful if you'd like to persist the XGBoost model as part of another R object.

Note: Do not use `xgb.serialize` to store models long-term. It persists not only the model but also internal configurations and parameters, and its format is not stable across multiple XGBoost versions. Use `xgb.serialize` only for checkpointing.

For more details and explanation about model persistence and archival, consult the page [https://xgboost.readthedocs.io/en/latest/tutorials/saving\\_model.html](https://xgboost.readthedocs.io/en/latest/tutorials/saving_model.html).

### Examples

```
data(agaricus.train, package='xgboost')
bst <- xgboost(data = agaricus.train$data, label = agaricus.train$label, max_depth = 2,
              eta = 1, nthread = 2, nrounds = 2, objective = "binary:logistic")

# Save as a stand-alone file; load it with xgb.load()
xgb.save(bst, 'xgb.model')
bst2 <- xgb.load('xgb.model')

# Save as a stand-alone file (JSON); load it with xgb.load()
xgb.save(bst, 'xgb.model.json')
bst2 <- xgb.load('xgb.model.json')
if (file.exists('xgb.model.json')) file.remove('xgb.model.json')

# Save as a raw byte vector; load it with xgb.load.raw()
xgb_bytes <- xgb.save.raw(bst)
bst2 <- xgb.load.raw(xgb_bytes)

# Persist XGBoost model as part of another R object
obj <- list(xgb_model_bytes = xgb.save.raw(bst), description = "My first XGBoost model")
# Persist the R object. Here, saveRDS() is okay, since it doesn't persist
# xgb.Booster directly. What's being persisted is the future-proof byte representation
# as given by xgb.save.raw().
saveRDS(obj, 'my_object.rds')
# Read back the R object
obj2 <- readRDS('my_object.rds')
# Re-construct xgb.Booster object from the bytes
bst2 <- xgb.load.raw(obj2$xgb_model_bytes)
if (file.exists('my_object.rds')) file.remove('my_object.rds')
```

---

agaricus.test

*Test part from Mushroom Data Set*

---

### Description

This data set is originally from the Mushroom data set, UCI Machine Learning Repository.

### Usage

```
data(agaricus.test)
```

### Format

A list containing a label vector, and a dgCMMatrix object with 1611 rows and 126 variables

**Details**

This data set includes the following fields:

- label the label for each record
- data a sparse Matrix of `dgCMatrix` class, with 126 columns.

**References**

<https://archive.ics.uci.edu/ml/datasets/Mushroom>

Bache, K. & Lichman, M. (2013). UCI Machine Learning Repository [<http://archive.ics.uci.edu/ml>]. Irvine, CA: University of California, School of Information and Computer Science.

---

|                |   |
|----------------|---|
| agaricus.train | <i>Training part from Mushroom Data Set</i> |
|----------------|---|

---

**Description**

This data set is originally from the Mushroom data set, UCI Machine Learning Repository.

**Usage**

```
data(agaricus.train)
```

**Format**

A list containing a label vector, and a `dgCMatrix` object with 6513 rows and 127 variables

**Details**

This data set includes the following fields:

- label the label for each record
- data a sparse Matrix of `dgCMatrix` class, with 126 columns.

**References**

<https://archive.ics.uci.edu/ml/datasets/Mushroom>

Bache, K. & Lichman, M. (2013). UCI Machine Learning Repository [<http://archive.ics.uci.edu/ml>]. Irvine, CA: University of California, School of Information and Computer Science.

---

`callbacks`*Callback closures for booster training.*

---

### Description

These are used to perform various service tasks either during boosting iterations or at the end. This approach helps to modularize many of such tasks without bloating the main training methods, and it offers .

### Details

By default, a callback function is run after each boosting iteration. An R-attribute `is_pre_iteration` could be set for a callback to define a pre-iteration function.

When a callback function has `finalize` parameter, its finalizer part will also be run after the boosting is completed.

WARNING: side-effects!!! Be aware that these callback functions access and modify things in the environment from which they are called from, which is a fairly uncommon thing to do in R.

To write a custom callback closure, make sure you first understand the main concepts about R environments. Check either R documentation on [environment](#) or the [Environments chapter](#) from the "Advanced R" book by Hadley Wickham. Further, the best option is to read the code of some of the existing callbacks - choose ones that do something similar to what you want to achieve. Also, you would need to get familiar with the objects available inside of the `xgb.train` and `xgb.cv` internal environments.

### See Also

[cb.print.evaluation](#), [cb.evaluation.log](#), [cb.reset.parameters](#), [cb.early.stop](#), [cb.save.model](#), [cb.cv.predict](#), [xgb.train](#), [xgb.cv](#)

---

`cb.cv.predict`*Callback closure for returning cross-validation based predictions.*

---

### Description

Callback closure for returning cross-validation based predictions.

### Usage

```
cb.cv.predict(save_models = FALSE)
```

### Arguments

`save_models` a flag for whether to save the folds' models.

## Details

This callback function saves predictions for all of the test folds, and also allows to save the folds' models.

It is a "finalizer" callback and it uses early stopping information whenever it is available, thus it must be run after the early stopping callback if the early stopping is used.

Callback function expects the following values to be set in its calling frame: `bst_folds`, `basket`, `data`, `end_iteration`, `params`, `num_parallel_tree`, `num_class`.

## Value

Predictions are returned inside of the `pred` element, which is either a vector or a matrix, depending on the number of prediction outputs per data row. The order of predictions corresponds to the order of rows in the original dataset. Note that when a custom `fold`s list is provided in `xgb.cv`, the predictions would only be returned properly when this list is a non-overlapping list of `k` sets of indices, as in a standard `k`-fold CV. The predictions would not be meaningful when user-provided folds have overlapping indices as in, e.g., random sampling splits. When some of the indices in the training dataset are not included into user-provided folds, their prediction value would be NA.

## See Also

[callbacks](#)

---

`cb.early.stop`

*Callback closure to activate the early stopping.*

---

## Description

Callback closure to activate the early stopping.

## Usage

```
cb.early.stop(  
  stopping_rounds,  
  maximize = FALSE,  
  metric_name = NULL,  
  verbose = TRUE  
)
```

## Arguments

`stopping_rounds`

The number of rounds with no improvement in the evaluation metric in order to stop the training.

`maximize`

whether to maximize the evaluation metric

|             |   |
|-------------|---|
| metric_name | the name of an evaluation column to use as a criteria for early stopping. If not set, the last column would be used. Let's say the test data in watchlist was labelled as dtest, and one wants to use the AUC in test data for early stopping regardless of where it is in the watchlist, then one of the following would need to be set: metric_name='dtest-auc' or metric_name='dtest_auc'. All dash '-' characters in metric names are considered equivalent to '_'. |
| verbose     | whether to print the early stopping information.  |

### Details

This callback function determines the condition for early stopping by setting the stop\_condition = TRUE flag in its calling frame.

The following additional fields are assigned to the model's R object:

- best\_score the evaluation score at the best iteration
- best\_iteration at which boosting iteration the best score has occurred (1-based index)

The Same values are also stored as xgb-attributes:

- best\_iteration is stored as a 0-based iteration index (for interoperability of binary models)
- best\_msg message string is also stored.

At least one data element is required in the evaluation watchlist for early stopping to work.

Callback function expects the following values to be set in its calling frame: stop\_condition, bst\_evaluation, rank, bst (or bst\_folds and basket), iteration, begin\_iteration, end\_iteration, num\_parallel\_tree.

### See Also

[callbacks](#), [xgb.attr](#)

---

cb.evaluation.log

*Callback closure for logging the evaluation history*

---

### Description

Callback closure for logging the evaluation history

### Usage

cb.evaluation.log()



**Details**

This callback function appends the current iteration evaluation results `bst_evaluation` available in the calling parent frame to the `evaluation_log` list in a calling frame.

The finalizer callback (called with `finalize = TRUE` in the end) converts the `evaluation_log` list into a final `data.table`.

The iteration evaluation result `bst_evaluation` must be a named numeric vector.

Note: in the column names of the final `data.table`, the dash '-' character is replaced with the underscore '\_' in order to make the column names more like regular R identifiers.

Callback function expects the following values to be set in its calling frame: `evaluation_log`, `bst_evaluation`, `iteration`.

**See Also**

[callbacks](#)

---

|                                  |  |
|----------------------------------|--|
| <code>cb.gblinear.history</code> | <i>Callback closure for collecting the model coefficients history of a gblinear booster during its training.</i> |
|----------------------------------|--|

---

**Description**

Callback closure for collecting the model coefficients history of a gblinear booster during its training.

**Usage**

```
cb.gblinear.history(sparse = FALSE)
```

**Arguments**

|                     |  |
|---------------------|--|
| <code>sparse</code> | when set to <code>FALSE/TRUE</code> , a dense/sparse matrix is used to store the result. Sparse format is useful when one expects only a subset of coefficients to be non-zero, when using the "thrifty" feature selector with fairly small number of top features selected per iteration. |
|---------------------|--|

**Details**

To keep things fast and simple, gblinear booster does not internally store the history of linear model coefficients at each boosting iteration. This callback provides a workaround for storing the coefficients' path, by extracting them after each training iteration.

Callback function expects the following values to be set in its calling frame: `bst` (or `bst_folds`).

**Value**

Results are stored in the `coefs` element of the closure. The `xgb.gblinear.history` convenience function provides an easy way to access it. With `xgb.train`, it is either a dense or a sparse matrix. While with `xgb.cv`, it is a list (an element per each fold) of such matrices.

**See Also**

[callbacks](#), [xgb.gblinear.history](#).

**Examples**

```
##### Binary classification:
#
# In the iris dataset, it is hard to linearly separate Versicolor class from the rest
# without considering the 2nd order interactions:
x <- model.matrix(Species ~ .^2, iris)[,-1]
colnames(x)
dtrain <- xgb.DMatrix(scale(x), label = 1*(iris$Species == "versicolor"))
param <- list(booster = "gblinear", objective = "reg:logistic", eval_metric = "auc",
             lambda = 0.0003, alpha = 0.0003, nthread = 2)
# For 'shotgun', which is a default linear updater, using high eta values may result in
# unstable behaviour in some datasets. With this simple dataset, however, the high learning
# rate does not break the convergence, but allows us to illustrate the typical pattern of
# "stochastic explosion" behaviour of this lock-free algorithm at early boosting iterations.
bst <- xgb.train(param, dtrain, list(tr=dtrain), nrounds = 200, eta = 1.,
               callbacks = list(cb.gblinear.history()))
# Extract the coefficients' path and plot them vs boosting iteration number:
coef_path <- xgb.gblinear.history(bst)
matplot(coef_path, type = 'l')

# With the deterministic coordinate descent updater, it is safer to use higher learning rates.
# Will try the classical componentwise boosting which selects a single best feature per round:
bst <- xgb.train(param, dtrain, list(tr=dtrain), nrounds = 200, eta = 0.8,
               updater = 'coord_descent', feature_selector = 'thrifty', top_k = 1,
               callbacks = list(cb.gblinear.history()))
matplot(xgb.gblinear.history(bst), type = 'l')
# Componentwise boosting is known to have similar effect to Lasso regularization.
# Try experimenting with various values of top_k, eta, nrounds,
# as well as different feature_selectors.

# For xgb.cv:
bst <- xgb.cv(param, dtrain, nfold = 5, nrounds = 100, eta = 0.8,
             callbacks = list(cb.gblinear.history()))
# coefficients in the CV fold #3
matplot(xgb.gblinear.history(bst)[[3]], type = 'l')

##### Multiclass classification:
#
dtrain <- xgb.DMatrix(scale(x), label = as.numeric(iris$Species) - 1)
param <- list(booster = "gblinear", objective = "multi:softprob", num_class = 3,
             lambda = 0.0003, alpha = 0.0003, nthread = 2)
# For the default linear updater 'shotgun' it sometimes is helpful
# to use smaller eta to reduce instability
bst <- xgb.train(param, dtrain, list(tr=dtrain), nrounds = 70, eta = 0.5,
               callbacks = list(cb.gblinear.history()))
# Will plot the coefficient paths separately for each class:
matplot(xgb.gblinear.history(bst, class_index = 0), type = 'l')
```

```
matplot(xgb.gblinear.history(bst, class_index = 1), type = 'l')
matplot(xgb.gblinear.history(bst, class_index = 2), type = 'l')

# CV:
bst <- xgb.cv(param, dtrain, nfold = 5, nrounds = 70, eta = 0.5,
             callbacks = list(cb.gblinear.history(FALSE)))
# 1st fold of 1st class
matplot(xgb.gblinear.history(bst, class_index = 0)[[1]], type = 'l')
```

---

cb.print.evaluation    *Callback closure for printing the result of evaluation*

---

## Description

Callback closure for printing the result of evaluation

## Usage

```
cb.print.evaluation(period = 1, showstd = TRUE)
```

## Arguments

|         |  |
|---------|--|
| period  | results would be printed every number of periods               |
| showstd | whether standard deviations should be printed (when available) |

## Details

The callback function prints the result of evaluation at every period iterations. The initial and the last iteration's evaluations are always printed.

Callback function expects the following values to be set in its calling frame: `bst_evaluation` (also `bst_evaluation_err` when available), `iteration`, `begin_iteration`, `end_iteration`.

## See Also

[callbacks](#)

---

cb.reset.parameters      *Callback closure for resetting the booster's parameters at each iteration.*

---

### Description

Callback closure for resetting the booster's parameters at each iteration.

### Usage

```
cb.reset.parameters(new_params)
```

### Arguments

`new_params`      a list where each element corresponds to a parameter that needs to be reset. Each element's value must be either a vector of values of length `nrounds` to be set at each iteration, or a function of two parameters `learning_rates(iteration, nrounds)` which returns a new parameter value by using the current iteration number and the total number of boosting rounds.

### Details

This is a "pre-iteration" callback function used to reset booster's parameters at the beginning of each iteration.

Note that when training is resumed from some previous model, and a function is used to reset a parameter value, the `nrounds` argument in this function would be the the number of boosting rounds in the current training.

Callback function expects the following values to be set in its calling frame: `bst` or `bst_folds`, `iteration`, `begin_iteration`, `end_iteration`.

### See Also

[callbacks](#)

---

cb.save.model      *Callback closure for saving a model file.*

---

### Description

Callback closure for saving a model file.

### Usage

```
cb.save.model(save_period = 0, save_name = "xgboost.model")
```

### Arguments

|             |   |
|-------------|---|
| save_period | save the model to disk after every save_period iterations; 0 means save the model at the end.   |
| save_name   | the name or path for the saved model file. It can contain a <code>sprintf</code> formatting specifier to include the integer iteration number in the file name. E.g., with save_name = 'xgboost_' the file saved at iteration 50 would be named "xgboost_0050.model". |

### Details

This callback function allows to save an xgb-model file, either periodically after each save\_period's or at the end.

Callback function expects the following values to be set in its calling frame: bst, iteration, begin\_iteration, end\_iteration.

### See Also

[callbacks](#)

---

|                 |                                  |
|-----------------|----------------------------------|
| dim.xgb.DMatrix | <i>Dimensions of xgb.DMatrix</i> |
|-----------------|----------------------------------|

---

### Description

Returns a vector of numbers of rows and of columns in an xgb.DMatrix.

### Usage

```
## S3 method for class 'xgb.DMatrix'  
dim(x)
```

### Arguments

|   |                             |
|---|-----------------------------|
| x | Object of class xgb.DMatrix |
|---|-----------------------------|

### Details

Note: since nrow and ncol internally use dim, they can also be directly used with an xgb.DMatrix object.

**Examples**

```

data(agaricus.train, package='xgboost')
train <- agaricus.train
dtrain <- xgb.DMatrix(train$data, label=train$label)

stopifnot(nrow(dtrain) == nrow(train$data))
stopifnot(ncol(dtrain) == ncol(train$data))
stopifnot(all(dim(dtrain) == dim(train$data)))

```

---

dimnames.xgb.DMatrix    *Handling of column names of xgb.DMatrix*

---

**Description**

Only column names are supported for `xgb.DMatrix`, thus setting of row names would have no effect and returned row names would be `NULL`.

**Usage**

```

## S3 method for class 'xgb.DMatrix'
dimnames(x)

## S3 replacement method for class 'xgb.DMatrix'
dimnames(x) <- value

```

**Arguments**

|                    |   |
|--------------------|---|
| <code>x</code>     | object of class <code>xgb.DMatrix</code>  |
| <code>value</code> | a list of two elements: the first one is ignored and the second one is column names |

**Details**

Generic `dimnames` methods are used by `colnames`. Since row names are irrelevant, it is recommended to use `colnames` directly.

**Examples**

```

data(agaricus.train, package='xgboost')
train <- agaricus.train
dtrain <- xgb.DMatrix(train$data, label=train$label)
dimnames(dtrain)
colnames(dtrain)
colnames(dtrain) <- make.names(1:ncol(train$data))
print(dtrain, verbose=TRUE)

```

---

`getinfo`*Get information of an `xgb.DMatrix` object*

---

## Description

Get information of an `xgb.DMatrix` object

## Usage

```
getinfo(object, ...)
```

```
## S3 method for class 'xgb.DMatrix'  
getinfo(object, name, ...)
```

## Arguments

|                     |  |
|---------------------|--|
| <code>object</code> | Object of class <code>xgb.DMatrix</code>               |
| <code>...</code>    | other parameters                                       |
| <code>name</code>   | the name of the information field to get (see details) |

## Details

The name field can be one of the following:

- `label`: label XGBoost learn from ;
- `weight`: to do a weight rescale ;
- `base_margin`: base margin is the base prediction XGBoost will boost from ;
- `nrow`: number of rows of the `xgb.DMatrix`.

`group` can be setup by `setinfo` but can't be retrieved by `getinfo`.

## Examples

```
data(agaricus.train, package='xgboost')  
dtrain <- with(agaricus.train, xgb.DMatrix(data, label = label))  
  
labels <- getinfo(dtrain, 'label')  
setinfo(dtrain, 'label', 1-labels)  
  
labels2 <- getinfo(dtrain, 'label')  
stopifnot(all(labels2 == 1-labels))
```

---

|           |   |
|-----------|---|
| normalize | <i>Scale feature value to have mean 0, standard deviation 1</i> |
|-----------|---|

---

**Description**

This is used to compare multiple features on the same plot. Internal utility function

**Usage**

```
normalize(x)
```

**Arguments**

|   |                |
|---|----------------|
| x | Numeric vector |
|---|----------------|

**Value**

Numeric vector with mean 0 and sd 1.

---

|                     |   |
|---------------------|---|
| predict.xgb.Booster | <i>Predict method for eXtreme Gradient Boosting model</i> |
|---------------------|---|

---

**Description**

Predicted values based on either xgboost model or model handle object.

**Usage**

```
## S3 method for class 'xgb.Booster'
predict(
  object,
  newdata,
  missing = NA,
  outputmargin = FALSE,
  ntreelimit = NULL,
  predleaf = FALSE,
  predcontrib = FALSE,
  approxcontrib = FALSE,
  predinteraction = FALSE,
  reshape = FALSE,
  training = FALSE,
  iterationrange = NULL,
  strict_shape = FALSE,
  ...
)

## S3 method for class 'xgb.Booster.handle'
predict(object, ...)
```



**Arguments**

|                 |   |
|-----------------|---|
| object          | Object of class <code>xgb.Booster</code> or <code>xgb.Booster.handle</code>   |
| newdata         | takes <code>matrix</code> , <code>dgCMatrix</code> , local data file or <code>xgb.DMatrix</code> .  |
| missing         | Missing is only used when input is dense matrix. Pick a float value that represents missing values in data (e.g., sometimes 0 or some other extreme value is used).   |
| outputmargin    | whether the prediction should be returned in the form of original untransformed sum of predictions from boosting iterations' results. E.g., setting <code>outputmargin=TRUE</code> for logistic regression would result in predictions for log-odds instead of probabilities.   |
| ntreelimit      | Deprecated, use <code>iterationrange</code> instead.  |
| predleaf        | whether predict leaf index.   |
| predcontrib     | whether to return feature contributions to individual predictions (see Details).  |
| approxcontrib   | whether to use a fast approximation for feature contributions (see Details).  |
| predinteraction | whether to return contributions of feature interactions to individual predictions (see Details).  |
| reshape         | whether to reshape the vector of predictions to a matrix form when there are several prediction outputs per case. This option has no effect when either of <code>predleaf</code> , <code>predcontrib</code> , or <code>predinteraction</code> flags is <code>TRUE</code> .  |
| training        | whether is the prediction result used for training. For dart booster, training predicting will perform dropout.   |
| iterationrange  | Specifies which layer of trees are used in prediction. For example, if a random forest is trained with 100 rounds. Specifying <code>'iteration_range=(1, 21)'</code> , then only the forests built during [1, 21) (half open set) rounds are used in this prediction. It's 1-based index just like R vector. When set to <code>c(1, 1)</code> XGBoost will use all trees. |
| strict_shape    | Default is <code>FALSE</code> . When it's set to <code>TRUE</code> , output type and shape of prediction are invariant to model type.   |
| ...             | Parameters passed to <code>predict.xgb.Booster</code>   |

**Details**

Note that `iterationrange` would currently do nothing for predictions from `gblinear`, since `gblinear` doesn't keep its boosting history.

One possible practical applications of the `predleaf` option is to use the model as a generator of new features which capture non-linearity and interactions, e.g., as implemented in [xgb.create.features](#).

Setting `predcontrib = TRUE` allows to calculate contributions of each feature to individual predictions. For "gblinear" booster, feature contributions are simply linear terms (`feature_beta * feature_value`). For "gbtree" booster, feature contributions are SHAP values (Lundberg 2017) that sum to the difference between the expected output of the model and the current prediction (where the hessian weights are used to compute the expectations). Setting `approxcontrib = TRUE` approximates these values following the idea explained in <http://blog.datadive.net/interpreting-random-forests/>.

With `predinteraction = TRUE`, SHAP values of contributions of interaction of each pair of features are computed. Note that this operation might be rather expensive in terms of compute and memory. Since it quadratically depends on the number of features, it is recommended to perform selection of the most important features first. See below about the format of the returned results.

## Value

The return type is different depending whether `strict_shape` is set to `TRUE`. By default, for regression or binary classification, it returns a vector of length `nrows(newdata)`. For multiclass classification, either a `num_class * nrows(newdata)` vector or a `(nrows(newdata), num_class)` dimension matrix is returned, depending on the `reshape` value.

When `predleaf = TRUE`, the output is a matrix object with the number of columns corresponding to the number of trees.

When `predcontrib = TRUE` and it is not a multiclass setting, the output is a matrix object with `num_features + 1` columns. The last "+ 1" column in a matrix corresponds to bias. For a multiclass case, a list of `num_class` elements is returned, where each element is such a matrix. The contribution values are on the scale of untransformed margin (e.g., for binary classification would mean that the contributions are log-odds deviations from bias).

When `predinteraction = TRUE` and it is not a multiclass setting, the output is a 3d array with dimensions `c(nrow, num_features + 1, num_features + 1)`. The off-diagonal (in the last two dimensions) elements represent different features interaction contributions. The array is symmetric WRT the last two dimensions. The "+ 1" columns corresponds to bias. Summing this array along the last dimension should produce practically the same result as predict with `predcontrib = TRUE`. For a multiclass case, a list of `num_class` elements is returned, where each element is such an array.

When `strict_shape` is set to `TRUE`, the output is always an array. For normal prediction, the output is a 2-dimension array (`num_class, nrow(newdata)`).

For `predcontrib = TRUE`, output is `(ncol(newdata) + 1, num_class, nrow(newdata))` For `predinteraction = TRUE`, output is `(ncol(newdata) + 1, ncol(newdata) + 1, num_class, nrow(newdata))` For `predleaf = TRUE`, output is `(n_trees_in_forest, num_class, n_iterations, nrow(newdata))`

## References

Scott M. Lundberg, Su-In Lee, "A Unified Approach to Interpreting Model Predictions", NIPS Proceedings 2017, <https://arxiv.org/abs/1705.07874>

Scott M. Lundberg, Su-In Lee, "Consistent feature attribution for tree ensembles", <https://arxiv.org/abs/1706.06060>

## See Also

[xgb.train](#).

## Examples

```
## binary classification:

data(agaricus.train, package='xgboost')
data(agaricus.test, package='xgboost')
train <- agaricus.train
```

```

test <- agaricus.test

bst <- xgboost(data = train$data, label = train$label, max_depth = 2,
              eta = 0.5, nthread = 2, nrounds = 5, objective = "binary:logistic")
# use all trees by default
pred <- predict(bst, test$data)
# use only the 1st tree
pred1 <- predict(bst, test$data, iterationrange = c(1, 2))

# Predicting tree leafs:
# the result is an nsamples X ntrees matrix
pred_leaf <- predict(bst, test$data, predleaf = TRUE)
str(pred_leaf)

# Predicting feature contributions to predictions:
# the result is an nsamples X (nfeatures + 1) matrix
pred_contr <- predict(bst, test$data, predcontrib = TRUE)
str(pred_contr)
# verify that contributions' sums are equal to log-odds of predictions (up to float precision):
summary(rowSums(pred_contr) - qlogis(pred))
# for the 1st record, let's inspect its features that had non-zero contribution to prediction:
contr1 <- pred_contr[1,]
contr1 <- contr1[-length(contr1)] # drop BIAS
contr1 <- contr1[contr1 != 0] # drop non-contributing features
contr1 <- contr1[order(abs(contr1))] # order by contribution magnitude
old_mar <- par("mar")
par(mar = old_mar + c(0,7,0,0))
barplot(contr1, horiz = TRUE, las = 2, xlab = "contribution to prediction in log-odds")
par(mar = old_mar)

## multiclass classification in iris dataset:

lb <- as.numeric(iris$Species) - 1
num_class <- 3
set.seed(11)
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]))
str(pred)
# 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
# the following should result in the same error as seen in the last iteration
sum(pred_labels != lb)/length(lb)

# compare that to the predictions from softmax:
set.seed(11)
bst <- xgboost(data = as.matrix(iris[, -5]), label = lb,
              max_depth = 4, eta = 0.5, nthread = 2, nrounds = 10, subsample = 0.5,

```

```
        objective = "multi:softmax", num_class = num_class)
pred <- predict(bst, as.matrix(iris[, -5]))
str(pred)
all.equal(pred, pred_labels)
# prediction from using only 5 iterations should result
# in the same error as seen in iteration 5:
pred5 <- predict(bst, as.matrix(iris[, -5]), iterationrange=c(1, 6))
sum(pred5 != lb)/length(lb)
```

---

prepare.ggplot.shap.data

*Combine and melt feature values and SHAP contributions for sample observations.*

---

## Description

Conforms to data format required for ggplot functions.

## Usage

```
prepare.ggplot.shap.data(data_list, normalize = FALSE)
```

## Arguments

|           |   |
|-----------|---|
| data_list | List containing 'data' and 'shap_contrib' returned by xgb.shap.data().  |
| normalize | Whether to standardize feature values to have mean 0 and standard deviation 1 (useful for comparing multiple features on the same plot). Default FALSE. |

## Details

Internal utility function.

## Value

A data.table containing the observation ID, the feature name, the feature value (normalized if specified), and the SHAP contribution value.

---

```
print.xgb.Booster      Print xgb.Booster
```

---

### Description

Print information about xgb.Booster.

### Usage

```
## S3 method for class 'xgb.Booster'  
print(x, verbose = FALSE, ...)
```

### Arguments

|         |   |
|---------|---|
| x       | an xgb.Booster object                                   |
| verbose | whether to print detailed data (e.g., attribute values) |
| ...     | not currently used                                      |

### Examples

```
data(agaricus.train, package='xgboost')  
train <- agaricus.train  
bst <- xgboost(data = train$data, label = train$label, max_depth = 2,  
              eta = 1, nthread = 2, nrounds = 2, objective = "binary:logistic")  
attr(bst, 'myattr') <- 'memo'  
  
print(bst)  
print(bst, verbose=TRUE)
```

---

```
print.xgb.cv.synchronous  
      Print xgb.cv result
```

---

### Description

Prints formatted results of xgb.cv.

### Usage

```
## S3 method for class 'xgb.cv.synchronous'  
print(x, verbose = FALSE, ...)
```

**Arguments**

|         |                                |
|---------|--------------------------------|
| x       | an xgb.cv. synchronous object  |
| verbose | whether to print detailed data |
| ...     | passed to data.table.print     |

**Details**

When not verbose, it would only print the evaluation results, including the best iteration (when available).

**Examples**

```
data(agaricus.train, package='xgboost')
train <- agaricus.train
cv <- xgb.cv(data = train$data, label = train$label, nfold = 5, max_depth = 2,
             eta = 1, nthread = 2, nrounds = 2, objective = "binary:logistic")
print(cv)
print(cv, verbose=TRUE)
```

---

```
print.xgb.DMatrix      Print xgb.DMatrix
```

---

**Description**

Print information about xgb.DMatrix. Currently it displays dimensions and presence of info-fields and colnames.

**Usage**

```
## S3 method for class 'xgb.DMatrix'
print(x, verbose = FALSE, ...)
```

**Arguments**

|         |  |
|---------|--|
| x       | an xgb.DMatrix object                    |
| verbose | whether to print colnames (when present) |
| ...     | not currently used                       |

**Examples**

```
data(agaricus.train, package='xgboost')
dtrain <- with(agaricus.train, xgb.DMatrix(data, label = label))

dtrain
print(dtrain, verbose=TRUE)
```

---

setinfo *Set information of an xgb.DMatrix object*

---

## Description

Set information of an xgb.DMatrix object

## Usage

```
setinfo(object, ...)  
  
## S3 method for class 'xgb.DMatrix'  
setinfo(object, name, info, ...)
```

## Arguments

|        |  |
|--------|--|
| object | Object of class "xgb.DMatrix"            |
| ...    | other parameters                         |
| name   | the name of the field to get             |
| info   | the specific field of information to set |

## Details

The name field can be one of the following:

- label: label XGBoost learn from ;
- weight: to do a weight rescale ;
- base\_margin: base margin is the base prediction XGBoost will boost from ;
- group: number of rows in each group (to use with rank:pairwise objective).

## Examples

```
data(agaricus.train, package='xgboost')  
dtrain <- with(agaricus.train, xgb.DMatrix(data, label = label))  
  
labels <- getinfo(dtrain, 'label')  
setinfo(dtrain, 'label', 1-labels)  
labels2 <- getinfo(dtrain, 'label')  
stopifnot(all.equal(labels2, 1-labels))
```

---

|       |   |
|-------|---|
| slice | <i>Get a new DMatrix containing the specified rows of original xgb.DMatrix object</i> |
|-------|---|

---

**Description**

Get a new DMatrix containing the specified rows of original xgb.DMatrix object

**Usage**

```
slice(object, ...)

## S3 method for class 'xgb.DMatrix'
slice(object, idxset, ...)

## S3 method for class 'xgb.DMatrix'
object[idxset, colset = NULL]
```

**Arguments**

|        |  |
|--------|--|
| object | Object of class "xgb.DMatrix"                            |
| ...    | other parameters (currently not used)                    |
| idxset | a integer vector of indices of rows needed               |
| colset | currently not used (columns subsetting is not available) |

**Examples**

```
data(agaricus.train, package='xgboost')
dtrain <- with(agaricus.train, xgb.DMatrix(data, label = label))

dsub <- slice(dtrain, 1:42)
labels1 <- getinfo(dsub, 'label')
dsub <- dtrain[1:42, ]
labels2 <- getinfo(dsub, 'label')
all.equal(labels1, labels2)
```

---

|          |  |
|----------|--|
| xgb.attr | <i>Accessors for serializable attributes of a model.</i> |
|----------|--|

---

**Description**

These methods allow to manipulate the key-value attribute strings of an xgboost model.



**Usage**

```
xgb.attr(object, name)

xgb.attr(object, name) <- value

xgb.attributes(object)

xgb.attributes(object) <- value
```

**Arguments**

|        |   |
|--------|---|
| object | Object of class <code>xgb.Booster</code> or <code>xgb.Booster.handle</code> .   |
| name   | a non-empty character string specifying which attribute is to be accessed.  |
| value  | a value of an attribute for <code>xgb.attr&lt;-</code> ; for <code>xgb.attributes&lt;-</code> it's a list (or an object coercible to a list) with the names of attributes to set and the elements corresponding to attribute values. Non-character values are converted to character. When attribute value is not a scalar, only the first index is used. Use <code>NULL</code> to remove an attribute. |

**Details**

The primary purpose of xgboost model attributes is to store some meta-data about the model. Note that they are a separate concept from the object attributes in R. Specifically, they refer to key-value strings that can be attached to an xgboost model, stored together with the model's binary representation, and accessed later (from R or any other interface). In contrast, any R-attribute assigned to an R-object of `xgb.Booster` class would not be saved by `xgb.save` because an xgboost model is an external memory object and its serialization is handled externally. Also, setting an attribute that has the same name as one of xgboost's parameters wouldn't change the value of that parameter for a model. Use `xgb.parameters<-` to set or change model parameters.

The attribute setters would usually work more efficiently for `xgb.Booster.handle` than for `xgb.Booster`, since only just a handle (pointer) would need to be copied. That would only matter if attributes need to be set many times. Note, however, that when feeding a handle of an `xgb.Booster` object to the attribute setters, the raw model cache of an `xgb.Booster` object would not be automatically updated, and it would be user's responsibility to call `xgb.serialize` to update it.

The `xgb.attributes<-` setter either updates the existing or adds one or several attributes, but it doesn't delete the other existing attributes.

**Value**

`xgb.attr` returns either a string value of an attribute or `NULL` if an attribute wasn't stored in a model.

`xgb.attributes` returns a list of all attribute stored in a model or `NULL` if a model has no stored attributes.

**Examples**

```
data(agaricus.train, package='xgboost')
train <- agaricus.train
```

```

bst <- xgboost(data = train$data, label = train$label, max_depth = 2,
              eta = 1, nthread = 2, nrounds = 2, objective = "binary:logistic")

xgb.attr(bst, "my_attribute") <- "my attribute value"
print(xgb.attr(bst, "my_attribute"))
xgb.attributes(bst) <- list(a = 123, b = "abc")

xgb.save(bst, 'xgb.model')
bst1 <- xgb.load('xgb.model')
if (file.exists('xgb.model')) file.remove('xgb.model')
print(xgb.attr(bst1, "my_attribute"))
print(xgb.attributes(bst1))

# deletion:
xgb.attr(bst1, "my_attribute") <- NULL
print(xgb.attributes(bst1))
xgb.attributes(bst1) <- list(a = NULL, b = NULL)
print(xgb.attributes(bst1))

```

---

xgb.Booster.complete *Restore missing parts of an incomplete xgb.Booster object.*

---

## Description

It attempts to complete an xgb.Booster object by restoring either its missing raw model memory dump (when it has no raw data but its xgb.Booster.handle is valid) or its missing internal handle (when its xgb.Booster.handle is not valid but it has a raw Booster memory dump).

## Usage

```
xgb.Booster.complete(object, saveraw = TRUE)
```

## Arguments

|         |   |
|---------|---|
| object  | object of class xgb.Booster   |
| saveraw | a flag indicating whether to append raw Booster memory dump data when it doesn't already exist. |

## Details

While this method is primarily for internal use, it might be useful in some practical situations.

E.g., when an xgb.Booster model is saved as an R object and then is loaded as an R object, its handle (pointer) to an internal xgboost model would be invalid. The majority of xgboost methods should still work for such a model object since those methods would be using xgb.Booster.complete internally. However, one might find it to be more efficient to call the xgb.Booster.complete function explicitly once after loading a model as an R-object. That would prevent further repeated implicit reconstruction of an internal booster model.

**Value**

An object of xgb.Booster class.

**Examples**

```
data(agaricus.train, package='xgboost')
bst <- xgboost(data = agaricus.train$data, label = agaricus.train$label, max_depth = 2,
              eta = 1, nthread = 2, nrounds = 2, objective = "binary:logistic")
saveRDS(bst, "xgb.model.rds")

# Warning: The resulting RDS file is only compatible with the current XGBoost version.
# Refer to the section titled "a-compatibility-note-for-saveRDS-save".
bst1 <- readRDS("xgb.model.rds")
if (file.exists("xgb.model.rds")) file.remove("xgb.model.rds")
# the handle is invalid:
print(bst1$handle)

bst1 <- xgb.Booster.complete(bst1)
# now the handle points to a valid internal booster model:
print(bst1$handle)
```

---

xgb.config

*Accessors for model parameters as JSON string.*


---

**Description**

Accessors for model parameters as JSON string.

**Usage**

```
xgb.config(object)
```

```
xgb.config(object) <- value
```

**Arguments**

|        |                             |
|--------|-----------------------------|
| object | Object of class xgb.Booster |
| value  | A JSON string.              |

**Examples**

```
data(agaricus.train, package='xgboost')
train <- agaricus.train

bst <- xgboost(data = train$data, label = train$label, max_depth = 2,
              eta = 1, nthread = 2, nrounds = 2, objective = "binary:logistic")
config <- xgb.config(bst)
```

---

xgb.create.features    *Create new features from a previously learned model*

---

### Description

May improve the learning by adding new features to the training data based on the decision trees from a previously learned model.

### Usage

```
xgb.create.features(model, data, ...)
```

### Arguments

|       |   |
|-------|---|
| model | decision tree boosting model learned on the original data |
| data  | original data (usually provided as a dgCMatrx matrix)     |
| ...   | currently not used  |

### Details

This is the function inspired from the paragraph 3.1 of the paper:

#### **Practical Lessons from Predicting Clicks on Ads at Facebook**

*(Xinran He, Junfeng Pan, Ou Jin, Tianbing Xu, Bo Liu, Tao Xu, Yan, xin Shi, Antoine Atallah, Ralf Herbrich, Stuart Bowers, Joaquin Quinonero Candela)*

International Workshop on Data Mining for Online Advertising (ADKDD) - August 24, 2014

<https://research.fb.com/publications/practical-lessons-from-predicting-clicks-on-ads-at-facebook/>.

Extract explaining the method:

"We found that boosted decision trees are a powerful and very convenient way to implement non-linear and tuple transformations of the kind we just described. We treat each individual tree as a categorical feature that takes as value the index of the leaf an instance ends up falling in. We use 1-of-K coding of this type of features.

For example, consider the boosted tree model in Figure 1 with 2 subtrees, where the first subtree has 3 leafs and the second 2 leafs. If an instance ends up in leaf 2 in the first subtree and leaf 1 in second subtree, the overall input to the linear classifier will be the binary vector  $[0, 1, 0, 1, 0]$ , where the first 3 entries correspond to the leaves of the first subtree and last 2 to those of the second subtree.

[...]

We can understand boosted decision tree based transformation as a supervised feature encoding that converts a real-valued vector into a compact binary-valued vector. A traversal from root node to a leaf node represents a rule on certain features."

### Value

dgCMatrx matrix including both the original data and the new features.

**Examples**

```

data(agaricus.train, package='xgboost')
data(agaricus.test, package='xgboost')
dtrain <- with(agaricus.train, xgb.DMatrix(data, label = label))
dtest <- with(agaricus.test, xgb.DMatrix(data, label = label))

param <- list(max_depth=2, eta=1, silent=1, objective='binary:logistic')
nrounds = 4

bst = xgb.train(params = param, data = dtrain, nrounds = nrounds, nthread = 2)

# Model accuracy without new features
accuracy.before <- sum((predict(bst, agaricus.test$data) >= 0.5) == agaricus.test$label) /
  length(agaricus.test$label)

# Convert previous features to one hot encoding
new.features.train <- xgb.create.features(model = bst, agaricus.train$data)
new.features.test <- xgb.create.features(model = bst, agaricus.test$data)

# learning with new features
new.dtrain <- xgb.DMatrix(data = new.features.train, label = agaricus.train$label)
new.dtest <- xgb.DMatrix(data = new.features.test, label = agaricus.test$label)
watchlist <- list(train = new.dtrain)
bst <- xgb.train(params = param, data = new.dtrain, nrounds = nrounds, nthread = 2)

# Model accuracy with new features
accuracy.after <- sum((predict(bst, new.dtest) >= 0.5) == agaricus.test$label) /
  length(agaricus.test$label)

# Here the accuracy was already good and is now perfect.
cat(paste("The accuracy was", accuracy.before, "before adding leaf features and it is now",
  accuracy.after, "!\n"))

```

---

xgb.cv

*Cross Validation*


---

**Description**

The cross validation function of xgboost

**Usage**

```

xgb.cv(
  params = list(),
  data,
  nrounds,
  nfold,
  label = NULL,

```

```

missing = NA,
prediction = FALSE,
showsd = TRUE,
metrics = list(),
obj = NULL,
feval = NULL,
stratified = TRUE,
folds = NULL,
train_folds = NULL,
verbose = TRUE,
print_every_n = 1L,
early_stopping_rounds = NULL,
maximize = NULL,
callbacks = list(),
...
)

```

## Arguments

|            |   |
|------------|---|
| params     | <p>the list of parameters. The complete list of parameters is available in the <a href="#">online documentation</a>. Below is a shorter summary:</p> <ul style="list-style-type: none"> <li>• objective objective function, common ones are <ul style="list-style-type: none"> <li>– reg:squarederror Regression with squared loss.</li> <li>– binary:logistic logistic regression for classification.</li> <li>– See <a href="#">xgb.train()</a> for complete list of objectives.</li> </ul> </li> <li>• eta step size of each boosting step</li> <li>• max_depth maximum depth of the tree</li> <li>• nthread number of thread used in training, if not set, all threads are used</li> </ul> <p>See <a href="#">xgb.train</a> for further details. See also <a href="#">demo/</a> for walkthrough example in R.</p> |
| data       | takes an <code>xgb.DMatrix</code> , <code>matrix</code> , or <code>dgCMatrix</code> as the input.   |
| nrounds    | the max number of iterations  |
| nfold      | the original dataset is randomly partitioned into <code>nfold</code> equal size subsamples.   |
| label      | vector of response values. Should be provided only when data is an R-matrix.  |
| missing    | is only used when input is a dense matrix. By default is set to NA, which means that NA values should be considered as 'missing' by the algorithm. Sometimes, 0 or other extreme value might be used to represent missing values.   |
| prediction | A logical value indicating whether to return the test fold predictions from each CV model. This parameter engages the <a href="#">cb.cv.predict</a> callback.   |
| showsd     | boolean, whether to show standard deviation of cross validation   |
| metrics,   | list of evaluation metrics to be used in cross validation, when it is not specified, the evaluation metric is chosen according to objective function. Possible options are: <ul style="list-style-type: none"> <li>• error binary classification error rate</li> </ul>  |

|                       |  |
|-----------------------|--|
|                       | <ul style="list-style-type: none"> <li>• rmse Rooted mean square error</li> <li>• logloss negative log-likelihood function</li> <li>• mae Mean absolute error</li> <li>• mape Mean absolute percentage error</li> <li>• auc Area under curve</li> <li>• aucpr Area under PR curve</li> <li>• merror Exact matching error, used to evaluate multi-class classification</li> </ul> |
| obj                   | customized objective function. Returns gradient and second order gradient with given prediction and dtrain.  |
| feval                 | customized evaluation function. Returns <code>list(metric='metric-name', value='metric-value')</code> with given prediction and dtrain.  |
| stratified            | a boolean indicating whether sampling of folds should be stratified by the values of outcome labels.   |
| folds                 | <code>list</code> provides a possibility to use a list of pre-defined CV folds (each element must be a vector of test fold's indices). When folds are supplied, the <code>nfold</code> and <code>stratified</code> parameters are ignored.   |
| train_folds           | <code>list</code> list specifying which indices to use for training. If NULL (the default) all indices not specified in <code>folds</code> will be used for training.  |
| verbose               | boolean, print the statistics during the process   |
| print_every_n         | Print each n-th iteration evaluation messages when <code>verbose&gt;0</code> . Default is 1 which means all messages are printed. This parameter is passed to the <code>cb.print.evaluation</code> callback.   |
| early_stopping_rounds | If NULL, the early stopping function is not triggered. If set to an integer k, training with a validation set will stop if the performance doesn't improve for k rounds. Setting this parameter engages the <code>cb.early.stop</code> callback.   |
| maximize              | If <code>feval</code> and <code>early_stopping_rounds</code> are set, then this parameter must be set as well. When it is TRUE, it means the larger the evaluation score the better. This parameter is passed to the <code>cb.early.stop</code> callback.  |
| callbacks             | a list of callback functions to perform various task during boosting. See <a href="#">callbacks</a> . Some of the callbacks are automatically created depending on the parameters' values. User can provide either existing or their own callback methods in order to customize the training process.  |
| ...                   | other parameters to pass to <code>params</code> .  |

## Details

The original sample is randomly partitioned into `nfold` equal size subsamples.

Of the `nfold` subsamples, a single subsample is retained as the validation data for testing the model, and the remaining `nfold - 1` subsamples are used as training data.

The cross-validation process is then repeated `nrounds` times, with each of the `nfold` subsamples used exactly once as the validation data.

All observations are used for both training and validation.

Adapted from [https://en.wikipedia.org/wiki/Cross-validation\\_%28statistics%29](https://en.wikipedia.org/wiki/Cross-validation_%28statistics%29)

**Value**

An object of class `xgb.cv`. synchronous with the following elements:

- `call` a function call.
- `params` parameters that were passed to the xgboost library. Note that it does not capture parameters changed by the `cb.reset.parameters` callback.
- `callbacks` callback functions that were either automatically assigned or explicitly passed.
- `evaluation_log` evaluation history stored as a `data.table` with the first column corresponding to iteration number and the rest corresponding to the CV-based evaluation means and standard deviations for the training and test CV-sets. It is created by the `cb.evaluation.log` callback.
- `niter` number of boosting iterations.
- `nfeatures` number of features in training data.
- `fold` the list of CV folds' indices - either those passed through the `fold`s parameter or randomly generated.
- `best_iteration` iteration number with the best evaluation metric value (only available with early stopping).
- `best_ntreelimit` and the `ntreelimit` Deprecated attributes, use `best_iteration` instead.
- `pred` CV prediction values available when `prediction` is set. It is either vector or matrix (see `cb.cv.predict`).
- `models` a list of the CV folds' models. It is only available with the explicit setting of the `cb.cv.predict(save_models = TRUE)` callback.

**Examples**

```
data(agaricus.train, package='xgboost')
dtrain <- with(agaricus.train, xgb.DMatrix(data, label = label))
cv <- xgb.cv(data = dtrain, nrounds = 3, nthread = 2, nfold = 5, metrics = list("rmse", "auc"),
            max_depth = 3, eta = 1, objective = "binary:logistic")
print(cv)
print(cv, verbose=TRUE)
```

---

xgb.DMatrix

*Construct xgb.DMatrix object*


---

**Description**

Construct `xgb.DMatrix` object from either a dense matrix, a sparse matrix, or a local file. Supported input file formats are either a LIBSVM text file or a binary file that was created previously by `xgb.DMatrix.save`.



**Usage**

```
xgb.DMatrix(
  data,
  info = list(),
  missing = NA,
  silent = FALSE,
  nthread = NULL,
  ...
)
```

**Arguments**

|         |   |
|---------|---|
| data    | a matrix object (either numeric or integer), a dgCMatix object, or a character string representing a filename.  |
| info    | a named list of additional information to store in the xgb.DMatrix object. See <a href="#">setinfo</a> for the specific allowed kinds of  |
| missing | a float value to represents missing values in data (used only when input is a dense matrix). It is useful when a 0 or some other extreme value represents missing values in data. |
| silent  | whether to suppress printing an informational message after loading from a file.  |
| nthread | Number of threads used for creating DMatrix.  |
| ...     | the info data could be passed directly as parameters, without creating an info list.  |

**Examples**

```
data(agaricus.train, package='xgboost')
dtrain <- with(agaricus.train, xgb.DMatrix(data, label = label))
xgb.DMatrix.save(dtrain, 'xgb.DMatrix.data')
dtrain <- xgb.DMatrix('xgb.DMatrix.data')
if (file.exists('xgb.DMatrix.data')) file.remove('xgb.DMatrix.data')
```

---

|                  |   |
|------------------|---|
| xgb.DMatrix.save | <i>Save xgb.DMatrix object to binary file</i> |
|------------------|---|

---

**Description**

Save xgb.DMatrix object to binary file

**Usage**

```
xgb.DMatrix.save(dmatrix, fname)
```

**Arguments**

|         |                                |
|---------|--------------------------------|
| dmatrix | the xgb.DMatrix object         |
| fname   | the name of the file to write. |

**Examples**

```
data(agaricus.train, package='xgboost')
dtrain <- with(agaricus.train, xgb.DMatrix(data, label = label))
xgb.DMatrix.save(dtrain, 'xgb.DMatrix.data')
dtrain <- xgb.DMatrix('xgb.DMatrix.data')
if (file.exists('xgb.DMatrix.data')) file.remove('xgb.DMatrix.data')
```

---

xgb.dump

*Dump an xgboost model in text format.*


---

**Description**

Dump an xgboost model in text format.

**Usage**

```
xgb.dump(
  model,
  fname = NULL,
  fmap = "",
  with_stats = FALSE,
  dump_format = c("text", "json"),
  ...
)
```

**Arguments**

|             |   |
|-------------|---|
| model       | the model object.   |
| fname       | the name of the text file where to save the model text dump. If not provided or set to NULL, the model is returned as a character vector.   |
| fmap        | feature map file representing feature types. Detailed description could be found at <a href="https://github.com/dmlc/xgboost/wiki/Binary-Classification#dump-model">https://github.com/dmlc/xgboost/wiki/Binary-Classification#dump-model</a> . See demo/ for walkthrough example in R, and <a href="https://github.com/dmlc/xgboost/blob/master/demo/data/featmap.txt">https://github.com/dmlc/xgboost/blob/master/demo/data/featmap.txt</a> for example Format. |
| with_stats  | whether to dump some additional statistics about the splits. When this option is on, the model dump contains two additional values: gain is the approximate loss function gain we get in each split; cover is the sum of second order gradient in each node.  |
| dump_format | either 'text' or 'json' format could be specified.  |
| ...         | currently not used  |

**Value**

If fname is not provided or set to NULL the function will return the model as a character vector. Otherwise it will return TRUE.

**Examples**

```

data(agaricus.train, package='xgboost')
data(agaricus.test, package='xgboost')
train <- agaricus.train
test <- agaricus.test
bst <- xgboost(data = train$data, label = train$label, max_depth = 2,
              eta = 1, nthread = 2, nrounds = 2, objective = "binary:logistic")
# save the model in file 'xgb.model.dump'
dump_path = file.path(tempdir(), 'model.dump')
xgb.dump(bst, dump_path, with_stats = TRUE)

# print the model without saving it to a file
print(xgb.dump(bst, with_stats = TRUE))

# print in JSON format:
cat(xgb.dump(bst, with_stats = TRUE, dump_format='json'))

```

---

`xgb.gblinear.history` *Extract gblinear coefficients history.*

---

**Description**

A helper function to extract the matrix of linear coefficients' history from a gblinear model created while using the `cb.gblinear.history()` callback.

**Usage**

```
xgb.gblinear.history(model, class_index = NULL)
```

**Arguments**

|                          |  |
|--------------------------|--|
| <code>model</code>       | either an <code>xgb.Booster</code> or a result of <code>xgb.cv()</code> , trained using the <code>cb.gblinear.history()</code> callback.   |
| <code>class_index</code> | zero-based class index to extract the coefficients for only that specific class in a multinomial multiclass model. When it is <code>NULL</code> , all the coefficients are returned. Has no effect in non-multiclass models. |

**Value**

For an `xgb.train` result, a matrix (either dense or sparse) with the columns corresponding to iteration's coefficients (in the order as `xgb.dump()` would return) and the rows corresponding to boosting iterations.

For an `xgb.cv` result, a list of such matrices is returned with the elements corresponding to CV folds.

---

xgb.ggplot.deepness *Plot model trees deepness*

---

### Description

Visualizes distributions related to depth of tree leafs. `xgb.plot.deepness` uses base R graphics, while `xgb.ggplot.deepness` uses the ggplot backend.

### Usage

```
xgb.ggplot.deepness(
  model = NULL,
  which = c("2x1", "max.depth", "med.depth", "med.weight")
)

xgb.plot.deepness(
  model = NULL,
  which = c("2x1", "max.depth", "med.depth", "med.weight"),
  plot = TRUE,
  ...
)
```

### Arguments

|                    |   |
|--------------------|---|
| <code>model</code> | either an <code>xgb.Booster</code> model generated by the <code>xgb.train</code> function or a <code>data.table</code> result of the <code>xgb.model.dt.tree</code> function. |
| <code>which</code> | which distribution to plot (see details).   |
| <code>plot</code>  | (base R <code>barplot</code> ) whether a <code>barplot</code> should be produced. If <code>FALSE</code> , only a <code>data.table</code> is returned.                         |
| <code>...</code>   | other parameters passed to <code>barplot</code> or <code>plot</code> .  |

### Details

When `which="2x1"`, two distributions with respect to the leaf depth are plotted on top of each other:

- the distribution of the number of leafs in a tree model at a certain depth;
- the distribution of average weighted number of observations ("cover") ending up in leafs at certain depth.

Those could be helpful in determining sensible ranges of the `max_depth` and `min_child_weight` parameters.

When `which="max.depth"` or `which="med.depth"`, plots of either maximum or median depth per tree with respect to tree number are created. And `which="med.weight"` allows to see how a tree's median absolute leaf weight changes through the iterations.

This function was inspired by the blog post <https://github.com/aysent/random-forest-leaf-visualization>.

**Value**

Other than producing plots (when `plot=TRUE`), the `xgb.plot.deepness` function silently returns a processed `data.table` where each row corresponds to a terminal leaf in a tree model, and contains information about leaf's depth, cover, and weight (which is used in calculating predictions).

The `xgb.ggplot.deepness` silently returns either a list of two ggplot graphs when `which="2x1"` or a single ggplot graph for the other which options.

**See Also**

[xgb.train](#), [xgb.model.dt.tree](#).

**Examples**

```
data(agaricus.train, package='xgboost')

# Change max_depth to a higher number to get a more significant result
bst <- xgboost(data = agaricus.train$data, label = agaricus.train$label, max_depth = 6,
              eta = 0.1, nthread = 2, nrounds = 50, objective = "binary:logistic",
              subsample = 0.5, min_child_weight = 2)

xgb.plot.deepness(bst)
xgb.ggplot.deepness(bst)

xgb.plot.deepness(bst, which='max.depth', pch=16, col=rgb(0,0,1,0.3), cex=2)

xgb.plot.deepness(bst, which='med.weight', pch=16, col=rgb(0,0,1,0.3), cex=2)
```

---

`xgb.ggplot.importance` *Plot feature importance as a bar graph*

---

**Description**

Represents previously calculated feature importance as a bar graph. `xgb.plot.importance` uses base R graphics, while `xgb.ggplot.importance` uses the ggplot backend.

**Usage**

```
xgb.ggplot.importance(
  importance_matrix = NULL,
  top_n = NULL,
  measure = NULL,
  rel_to_first = FALSE,
  n_clusters = c(1:10),
  ...
)
```

```
xgb.plot.importance(
  importance_matrix = NULL,
  top_n = NULL,
  measure = NULL,
  rel_to_first = FALSE,
  left_margin = 10,
  cex = NULL,
  plot = TRUE,
  ...
)
```

### Arguments

|                                |  |
|--------------------------------|--|
| <code>importance_matrix</code> | a <code>data.table</code> returned by <code>xgb.importance</code> .  |
| <code>top_n</code>             | maximal number of top features to include into the plot.   |
| <code>measure</code>           | the name of importance measure to plot. When <code>NULL</code> , 'Gain' would be used for trees and 'Weight' would be used for gblinear.                                     |
| <code>rel_to_first</code>      | whether importance values should be represented as relative to the highest ranked feature. See Details.  |
| <code>n_clusters</code>        | (ggplot only) a numeric vector containing the min and the max range of the possible number of clusters of bars.  |
| <code>...</code>               | other parameters passed to <code>barplot</code> (except <code>horiz</code> , <code>border</code> , <code>cex.names</code> , <code>names.arg</code> , and <code>las</code> ). |
| <code>left_margin</code>       | (base R barplot) allows to adjust the left margin size to fit feature names. When it is <code>NULL</code> , the existing <code>par('mar')</code> is used.                    |
| <code>cex</code>               | (base R barplot) passed as <code>cex.names</code> parameter to <code>barplot</code> .  |
| <code>plot</code>              | (base R barplot) whether a barplot should be produced. If <code>FALSE</code> , only a <code>data.table</code> is returned.   |

### Details

The graph represents each feature as a horizontal bar of length proportional to the importance of a feature. Features are shown ranked in a decreasing importance order. It works for importances from both gblinear and gbtree models.

When `rel_to_first = FALSE`, the values would be plotted as they were in `importance_matrix`. For gbtree model, that would mean being normalized to the total of 1 ("what is feature's importance contribution relative to the whole model?"). For linear models, `rel_to_first = FALSE` would show actual values of the coefficients. Setting `rel_to_first = TRUE` allows to see the picture from the perspective of "what is feature's importance contribution relative to the most important feature?"

The ggplot-backend method also performs 1-D clustering of the importance values, with bar colors corresponding to different clusters that have somewhat similar importance values.

**Value**

The `xgb.plot.importance` function creates a barplot (when `plot=TRUE`) and silently returns a processed `data.table` with `n_top` features sorted by importance.

The `xgb.ggplot.importance` function returns a `ggplot` graph which could be customized afterwards. E.g., to change the title of the graph, add `+ ggtitle("A GRAPH NAME")` to the result.

**See Also**

[barplot](#).

**Examples**

```
data(agaricus.train)

bst <- xgboost(data = agaricus.train$data, label = agaricus.train$label, max_depth = 3,
              eta = 1, nthread = 2, nrounds = 2, objective = "binary:logistic")

importance_matrix <- xgb.importance(colnames(agaricus.train$data), model = bst)

xgb.plot.importance(importance_matrix, rel_to_first = TRUE, xlab = "Relative importance")

(gg <- xgb.ggplot.importance(importance_matrix, measure = "Frequency", rel_to_first = TRUE))
gg + ggplot2::ylab("Frequency")
```

---

`xgb.ggplot.shap.summary`

*SHAP contribution dependency summary plot*

---

**Description**

Compare SHAP contributions of different features.

**Usage**

```
xgb.ggplot.shap.summary(
  data,
  shap_contrib = NULL,
  features = NULL,
  top_n = 10,
  model = NULL,
  trees = NULL,
  target_class = NULL,
  approxcontrib = FALSE,
  subsample = NULL
)
```

```
xgb.plot.shap.summary(
  data,
  shap_contrib = NULL,
  features = NULL,
  top_n = 10,
  model = NULL,
  trees = NULL,
  target_class = NULL,
  approxcontrib = FALSE,
  subsample = NULL
)
```

### Arguments

|               |  |
|---------------|--|
| data          | data as a matrix or dgCMatrix.   |
| shap_contrib  | a matrix of SHAP contributions that was computed earlier for the above data. When it is NULL, it is computed internally using model and data.  |
| features      | a vector of either column indices or of feature names to plot. When it is NULL, feature importance is calculated, and top_n high ranked features are taken.  |
| top_n         | when features is NULL, top_n [1, 100] most important features in a model are taken.  |
| model         | an xgb.Booster model. It has to be provided when either shap_contrib or features is missing.   |
| trees         | passed to <a href="#">xgb.importance</a> when features = NULL.   |
| target_class  | is only relevant for multiclass models. When it is set to a 0-based class index, only SHAP contributions for that specific class are used. If it is not set, SHAP importances are averaged over all classes. |
| approxcontrib | passed to <a href="#">predict.xgb.Booster</a> when shap_contrib = NULL.  |
| subsample     | a random fraction of data points to use for plotting. When it is NULL, it is set so that up to 100K data points are used.  |

### Details

A point plot (each point representing one sample from data) is produced for each feature, with the points plotted on the SHAP value axis. Each point (observation) is coloured based on its feature value. The plot hence allows us to see which features have a negative / positive contribution on the model prediction, and whether the contribution is different for larger or smaller values of the feature. We effectively try to replicate the `summary_plot` function from <https://github.com/slundberg/shap>.

### Value

A ggplot2 object.

### See Also

[xgb.plot.shap](#), [xgb.ggplot.shap.summary](#), <https://github.com/slundberg/shap>



**Examples**

```
# See \code{\link{xgb.plot.shap}}.
```

---

|                |   |
|----------------|---|
| xgb.importance | <i>Importance of features in a model.</i> |
|----------------|---|

---

**Description**

Creates a data table of feature importances in a model.

**Usage**

```
xgb.importance(
  feature_names = NULL,
  model = NULL,
  trees = NULL,
  data = NULL,
  label = NULL,
  target = NULL
)
```

**Arguments**

|               |   |
|---------------|---|
| feature_names | character vector of feature names. If the model already contains feature names, those would be used when feature_names=NULL (default value). Non-null feature_names could be provided to override those in the model.   |
| model         | object of class xgb.Booster.  |
| trees         | (only for the gtree booster) an integer vector of tree indices that should be included into the importance calculation. If set to NULL, all trees of the model are parsed. It could be useful, e.g., in multiclass classification to get feature importances for each class separately. <b>IMPORTANT:</b> the tree index in xgboost models is zero-based (e.g., use trees = 0:4 for first 5 trees). |
| data          | deprecated.   |
| label         | deprecated.   |
| target        | deprecated.   |

**Details**

This function works for both linear and tree models.

For linear models, the importance is the absolute magnitude of linear coefficients. For that reason, in order to obtain a meaningful ranking by importance for a linear model, the features need to be on the same scale (which you also would want to do when using either L1 or L2 regularization).

**Value**

For a tree model, a `data.table` with the following columns:

- Features names of the features used in the model;
- Gain represents fractional contribution of each feature to the model based on the total gain of this feature's splits. Higher percentage means a more important predictive feature.
- Cover metric of the number of observation related to this feature;
- Frequency percentage representing the relative number of times a feature have been used in trees.

A linear model's importance `data.table` has the following columns:

- Features names of the features used in the model;
- Weight the linear coefficient of this feature;
- Class (only for multiclass models) class label.

If `feature_names` is not provided and `model` doesn't have `feature_names`, index of the features will be used instead. Because the index is extracted from the model dump (based on C++ code), it starts at 0 (as in C/C++ or Python) instead of 1 (usual in R).

**Examples**

```
# binomial classification using gbtree:
data(agaricus.train, package='xgboost')
bst <- xgboost(data = agaricus.train$data, label = agaricus.train$label, max_depth = 2,
              eta = 1, nthread = 2, nrounds = 2, objective = "binary:logistic")
xgb.importance(model = bst)

# binomial classification using gblinear:
bst <- xgboost(data = agaricus.train$data, label = agaricus.train$label, booster = "gblinear",
              eta = 0.3, nthread = 1, nrounds = 20, objective = "binary:logistic")
xgb.importance(model = bst)

# multiclass classification using gbtree:
nclass <- 3
nrounds <- 10
mbst <- xgboost(data = as.matrix(iris[, -5]), label = as.numeric(iris$Species) - 1,
               max_depth = 3, eta = 0.2, nthread = 2, nrounds = nrounds,
               objective = "multi:softprob", num_class = nclass)
# all classes clumped together:
xgb.importance(model = mbst)
# inspect importances separately for each class:
xgb.importance(model = mbst, trees = seq(from=0, by=nclass, length.out=nrounds))
xgb.importance(model = mbst, trees = seq(from=1, by=nclass, length.out=nrounds))
xgb.importance(model = mbst, trees = seq(from=2, by=nclass, length.out=nrounds))

# multiclass classification using gblinear:
mbst <- xgboost(data = scale(as.matrix(iris[, -5])), label = as.numeric(iris$Species) - 1,
               booster = "gblinear", eta = 0.2, nthread = 1, nrounds = 15,
```

```
        objective = "multi:softprob", num_class = nclass)
xgb.importance(model = mbst)
```

---

|          |  |
|----------|--|
| xgb.load | <i>Load xgboost model from binary file</i> |
|----------|--|

---

## Description

Load xgboost model from the binary model file.

## Usage

```
xgb.load(modelfile)
```

## Arguments

modelfile        the name of the binary input file.

## Details

The input file is expected to contain a model saved in an xgboost-internal binary format using either [xgb.save](#) or [cb.save.model](#) in R, or using some appropriate methods from other xgboost interfaces. E.g., a model trained in Python and saved from there in xgboost format, could be loaded from R.

Note: a model saved as an R-object, has to be loaded using corresponding R-methods, not `xgb.load`.

## Value

An object of `xgb.Booster` class.

## See Also

[xgb.save](#), [xgb.Booster.complete](#).

## Examples

```
data(agaricus.train, package='xgboost')
data(agaricus.test, package='xgboost')
train <- agaricus.train
test <- agaricus.test
bst <- xgboost(data = train$data, label = train$label, max_depth = 2,
              eta = 1, nthread = 2, nrounds = 2, objective = "binary:logistic")
xgb.save(bst, 'xgb.model')
bst <- xgb.load('xgb.model')
if (file.exists('xgb.model')) file.remove('xgb.model')
pred <- predict(bst, test$data)
```

---

|              |  |
|--------------|--|
| xgb.load.raw | <i>Load serialised xgboost model from R's raw vector</i> |
|--------------|--|

---

**Description**

User can generate raw memory buffer by calling xgb.save.raw

**Usage**

```
xgb.load.raw(buffer)
```

**Arguments**

|        |                                     |
|--------|-------------------------------------|
| buffer | the buffer returned by xgb.save.raw |
|--------|-------------------------------------|

---

|                   |   |
|-------------------|---|
| xgb.model.dt.tree | <i>Parse a boosted tree model text dump</i> |
|-------------------|---|

---

**Description**

Parse a boosted tree model text dump into a data.table structure.

**Usage**

```
xgb.model.dt.tree(
  feature_names = NULL,
  model = NULL,
  text = NULL,
  trees = NULL,
  use_int_id = FALSE,
  ...
)
```

**Arguments**

|               |  |
|---------------|--|
| feature_names | character vector of feature names. If the model already contains feature names, those would be used when feature_names=NULL (default value). Non-null feature_names could be provided to override those in the model.  |
| model         | object of class xgb.Booster  |
| text          | character vector previously generated by the xgb.dump function (where parameter with_stats = TRUE should have been set). text takes precedence over model.   |
| trees         | an integer vector of tree indices that should be parsed. If set to NULL, all trees of the model are parsed. It could be useful, e.g., in multiclass classification to get only the trees of one certain class. <b>IMPORTANT:</b> the tree index in xgboost models is zero-based (e.g., use trees = 0:4 for first 5 trees). |

|            |  |
|------------|--|
| use_int_id | a logical flag indicating whether nodes in columns "Yes", "No", "Missing" should be represented as integers (when FALSE) or as "Tree-Node" character strings (when FALSE). |
| ...        | currently not used.  |

### Value

A data.table with detailed information about model trees' nodes.

The columns of the data.table are:

- Tree: integer ID of a tree in a model (zero-based index)
- Node: integer ID of a node in a tree (zero-based index)
- ID: character identifier of a node in a model (only when use\_int\_id=FALSE)
- Feature: for a branch node, it's a feature id or name (when available); for a leaf node, it simply labels it as 'Leaf'
- Split: location of the split for a branch node (split condition is always "less than")
- Yes: ID of the next node when the split condition is met
- No: ID of the next node when the split condition is not met
- Missing: ID of the next node when branch value is missing
- Quality: either the split gain (change in loss) or the leaf value
- Cover: metric related to the number of observation either seen by a split or collected by a leaf during training.

When use\_int\_id=FALSE, columns "Yes", "No", and "Missing" point to model-wide node identifiers in the "ID" column. When use\_int\_id=TRUE, those columns point to node identifiers from the corresponding trees in the "Node" column.

### Examples

```
# Basic use:

data(agaricus.train, package='xgboost')

bst <- xgboost(data = agaricus.train$data, label = agaricus.train$label, max_depth = 2,
              eta = 1, nthread = 2, nrounds = 2, objective = "binary:logistic")

(dt <- xgb.model.dt.tree(colnames(agaricus.train$data), bst))

# This bst model already has feature_names stored with it, so those would be used when
# feature_names is not set:
(dt <- xgb.model.dt.tree(model = bst))

# How to match feature names of splits that are following a current 'Yes' branch:

merge(dt, dt[, .(ID, Y.Feature=Feature)], by.x='Yes', by.y='ID', all.x=TRUE)[order(Tree,Node)]
```

---

xgb.parameters<-      *Accessors for model parameters.*

---

### Description

Only the setter for xgboost parameters is currently implemented.

### Usage

```
xgb.parameters(object) <- value
```

### Arguments

|        |   |
|--------|---|
| object | Object of class xgb.Booster or xgb.Booster.handle.  |
| value  | a list (or an object coercible to a list) with the names of parameters to set and the elements corresponding to parameter values. |

### Details

Note that the setter would usually work more efficiently for xgb.Booster.handle than for xgb.Booster, since only just a handle would need to be copied.

### Examples

```
data(agaricus.train, package='xgboost')
train <- agaricus.train

bst <- xgboost(data = train$data, label = train$label, max_depth = 2,
              eta = 1, nthread = 2, nrounds = 2, objective = "binary:logistic")

xgb.parameters(bst) <- list(eta = 0.1)
```

---

xgb.plot.multi.trees      *Project all trees on one tree and plot it*

---

### Description

Visualization of the ensemble of trees as a single collective unit.

## Usage

```
xgb.plot.multi.trees(  
  model,  
  feature_names = NULL,  
  features_keep = 5,  
  plot_width = NULL,  
  plot_height = NULL,  
  render = TRUE,  
  ...  
)
```

## Arguments

|               |  |
|---------------|--|
| model         | produced by the <code>xgb.train</code> function.                                   |
| feature_names | names of each feature as a character vector.                                       |
| features_keep | number of features to keep in each position of the multi trees.                    |
| plot_width    | width in pixels of the graph to produce  |
| plot_height   | height in pixels of the graph to produce   |
| render        | a logical flag for whether the graph should be rendered (see <code>Value</code> ). |
| ...           | currently not used   |

## Details

This function tries to capture the complexity of a gradient boosted tree model in a cohesive way by compressing an ensemble of trees into a single tree-graph representation. The goal is to improve the interpretability of a model generally seen as black box.

Note: this function is applicable to tree booster-based models only.

It takes advantage of the fact that the shape of a binary tree is only defined by its depth (therefore, in a boosting model, all trees have similar shape).

Moreover, the trees tend to reuse the same features.

The function projects each tree onto one, and keeps for each position the `features_keep` first features (based on the Gain per feature measure).

This function is inspired by this blog post: <https://wellecks.wordpress.com/2015/02/21/peering-into-the-black-box-visualizing-lambdamart/>

## Value

When `render = TRUE`: returns a rendered graph object which is an `htmlwidget` of class `grViz`. Similar to `ggplot` objects, it needs to be printed to see it when not running from command line.

When `render = FALSE`: silently returns a graph object which is of `DiagrammeR`'s class `dgr_graph`. This could be useful if one wants to modify some of the graph attributes before rendering the graph with `render_graph`.

## Examples

```

data(agaricus.train, package='xgboost')

bst <- xgboost(data = agaricus.train$data, label = agaricus.train$label, max_depth = 15,
              eta = 1, nthread = 2, nrounds = 30, objective = "binary:logistic",
              min_child_weight = 50, verbose = 0)

p <- xgb.plot.multi.trees(model = bst, features_keep = 3)
print(p)

## Not run:
# Below is an example of how to save this plot to a file.
# Note that for `export_graph` to work, the DiagrammeRsvg and rsvg packages must also be installed.
library(DiagrammeR)
gr <- xgb.plot.multi.trees(model=bst, features_keep = 3, render=FALSE)
export_graph(gr, 'tree.pdf', width=1500, height=600)

## End(Not run)

```

---

xgb.plot.shap

*SHAP contribution dependency plots*


---

## Description

Visualizing the SHAP feature contribution to prediction dependencies on feature value.

## Usage

```

xgb.plot.shap(
  data,
  shap_contrib = NULL,
  features = NULL,
  top_n = 1,
  model = NULL,
  trees = NULL,
  target_class = NULL,
  approxcontrib = FALSE,
  subsample = NULL,
  n_col = 1,
  col = rgb(0, 0, 1, 0.2),
  pch = ".",
  discrete_n_uniq = 5,
  discrete_jitter = 0.01,
  ylab = "SHAP",
  plot_NA = TRUE,
  col_NA = rgb(0.7, 0, 1, 0.6),

```



```

    pch_NA = ".",
    pos_NA = 1.07,
    plot_loess = TRUE,
    col_loess = 2,
    span_loess = 0.5,
    which = c("1d", "2d"),
    plot = TRUE,
    ...
)

```

### Arguments

|                 |  |
|-----------------|--|
| data            | data as a matrix or dgCMatrix.   |
| shap_contrib    | a matrix of SHAP contributions that was computed earlier for the above data. When it is NULL, it is computed internally using model and data.  |
| features        | a vector of either column indices or of feature names to plot. When it is NULL, feature importance is calculated, and top_n high ranked features are taken.  |
| top_n           | when features is NULL, top_n [1, 100] most important features in a model are taken.  |
| model           | an xgb.Booster model. It has to be provided when either shap_contrib or features is missing.   |
| trees           | passed to <a href="#">xgb.importance</a> when features = NULL.   |
| target_class    | is only relevant for multiclass models. When it is set to a 0-based class index, only SHAP contributions for that specific class are used. If it is not set, SHAP importances are averaged over all classes. |
| approxcontrib   | passed to <a href="#">predict.xgb.Booster</a> when shap_contrib = NULL.  |
| subsample       | a random fraction of data points to use for plotting. When it is NULL, it is set so that up to 100K data points are used.  |
| n_col           | a number of columns in a grid of plots.  |
| col             | color of the scatterplot markers.  |
| pch             | scatterplot marker.  |
| discrete_n_uniq | a maximal number of unique values in a feature to consider it as discrete.   |
| discrete_jitter | an amount parameter of jitter added to discrete features' positions.   |
| ylab            | a y-axis label in 1D plots.  |
| plot_NA         | whether the contributions of cases with missing values should also be plotted.   |
| col_NA          | a color of marker for missing value contributions.   |
| pch_NA          | a marker type for NA values.   |
| pos_NA          | a relative position of the x-location where NA values are shown: $\min(x) + (\max(x) - \min(x)) * \text{pos\_NA}$ .  |
| plot_loess      | whether to plot loess-smoothed curves. The smoothing is only done for features with more than 5 distinct values.   |

|            |  |
|------------|--|
| col_loess  | a color to use for the loess curves.   |
| span_loess | the span parameter in <code>loess</code> 's call.                                    |
| which      | whether to do univariate or bivariate plotting. NOTE: only 1D is implemented so far. |
| plot       | whether a plot should be drawn. If FALSE, only a list of matrices is returned.       |
| ...        | other parameters passed to <code>plot</code> .                                       |

### Details

These scatterplots represent how SHAP feature contributions depend of feature values. The similarity to partial dependency plots is that they also give an idea for how feature values affect predictions. However, in partial dependency plots, we usually see marginal dependencies of model prediction on feature value, while SHAP contribution dependency plots display the estimated contributions of a feature to model prediction for each individual case.

When `plot_loess = TRUE` is set, feature values are rounded to 3 significant digits and weighted LOESS is computed and plotted, where weights are the numbers of data points at each rounded value.

Note: SHAP contributions are shown on the scale of model margin. E.g., for a logistic binomial objective, the margin is prediction before a sigmoidal transform into probability-like values. Also, since SHAP stands for "SHapley Additive exPlanation" (model prediction = sum of SHAP contributions for all features + bias), depending on the objective used, transforming SHAP contributions for a feature from the marginal to the prediction space is not necessarily a meaningful thing to do.

### Value

In addition to producing plots (when `plot=TRUE`), it silently returns a list of two matrices:

- `data` the values of selected features;
- `shap_contrib` the contributions of selected features.

### References

Scott M. Lundberg, Su-In Lee, "A Unified Approach to Interpreting Model Predictions", NIPS Proceedings 2017, <https://arxiv.org/abs/1705.07874>

Scott M. Lundberg, Su-In Lee, "Consistent feature attribution for tree ensembles", <https://arxiv.org/abs/1706.06060>

### Examples

```
data(agaricus.train, package='xgboost')
data(agaricus.test, package='xgboost')

bst <- xgboost(agaricus.train$data, agaricus.train$label, nrounds = 50,
              eta = 0.1, max_depth = 3, subsample = .5,
              method = "hist", objective = "binary:logistic", nthread = 2, verbose = 0)

xgb.plot.shap(agaricus.test$data, model = bst, features = "odor=none")
```

```

contr <- predict(bst, agaricus.test$data, predcontrib = TRUE)
xgb.plot.shap(agaricus.test$data, contr, model = bst, top_n = 12, n_col = 3)
xgb.ggplot.shap.summary(agaricus.test$data, contr, model = bst, top_n = 12) # Summary plot

# multiclass example - plots for each class separately:
nclass <- 3
nrounds <- 20
x <- as.matrix(iris[, -5])
set.seed(123)
is.na(x[sample(nrow(x) * 4, 30)]) <- TRUE # introduce some missing values
mbst <- xgboost(data = x, label = as.numeric(iris$Species) - 1, nrounds = nrounds,
               max_depth = 2, eta = 0.3, subsample = .5, nthread = 2,
               objective = "multi:softprob", num_class = nclass, verbose = 0)
trees0 <- seq(from=0, by=nclass, length.out=nrounds)
col <- rgb(0, 0, 1, 0.5)
xgb.plot.shap(x, model = mbst, trees = trees0, target_class = 0, top_n = 4,
             n_col = 2, col = col, pch = 16, pch_NA = 17)
xgb.plot.shap(x, model = mbst, trees = trees0 + 1, target_class = 1, top_n = 4,
             n_col = 2, col = col, pch = 16, pch_NA = 17)
xgb.plot.shap(x, model = mbst, trees = trees0 + 2, target_class = 2, top_n = 4,
             n_col = 2, col = col, pch = 16, pch_NA = 17)
xgb.ggplot.shap.summary(x, model = mbst, target_class = 0, top_n = 4) # Summary plot

```

---

xgb.plot.tree

*Plot a boosted tree model*


---

## Description

Read a tree model text dump and plot the model.

## Usage

```

xgb.plot.tree(
  feature_names = NULL,
  model = NULL,
  trees = NULL,
  plot_width = NULL,
  plot_height = NULL,
  render = TRUE,
  show_node_id = FALSE,
  ...
)

```

## Arguments

**feature\_names** names of each feature as a character vector.  
**model** produced by the `xgb.train` function.

|              |  |
|--------------|--|
| trees        | an integer vector of tree indices that should be visualized. If set to NULL, all trees of the model are included. <b>IMPORTANT:</b> the tree index in xgboost model is zero-based (e.g., use <code>trees = 0:2</code> for the first 3 trees in a model). |
| plot_width   | the width of the diagram in pixels.  |
| plot_height  | the height of the diagram in pixels.   |
| render       | a logical flag for whether the graph should be rendered (see Value).   |
| show_node_id | a logical flag for whether to show node id's in the graph.   |
| ...          | currently not used.  |

### Details

The content of each node is organised that way:

- Feature name.
- Cover: The sum of second order gradient of training data classified to the leaf. If it is square loss, this simply corresponds to the number of instances seen by a split or collected by a leaf during training. The deeper in the tree a node is, the lower this metric will be.
- Gain (for split nodes): the information gain metric of a split (corresponds to the importance of the node in the model).
- Value (for leafs): the margin value that the leaf may contribute to prediction.

The tree root nodes also indicate the Tree index (0-based).

The "Yes" branches are marked by the "< split\_value" label. The branches that also used for missing values are marked as bold (as in "carrying extra capacity").

This function uses [GraphViz](#) as a backend of [DiagrammeR](#).

### Value

When `render = TRUE`: returns a rendered graph object which is an `htmlwidget` of class `grViz`. Similar to `ggplot` objects, it needs to be printed to see it when not running from command line.

When `render = FALSE`: silently returns a graph object which is of [DiagrammeR](#)'s class `dgr_graph`. This could be useful if one wants to modify some of the graph attributes before rendering the graph with [render\\_graph](#).

### Examples

```
data(agaricus.train, package='xgboost')

bst <- xgboost(data = agaricus.train$data, label = agaricus.train$label, max_depth = 3,
              eta = 1, nthread = 2, nrounds = 2, objective = "binary:logistic")
# plot all the trees
xgb.plot.tree(model = bst)
# plot only the first tree and display the node ID:
xgb.plot.tree(model = bst, trees = 0, show_node_id = TRUE)

## Not run:
# Below is an example of how to save this plot to a file.
```

```
# Note that for `export_graph` to work, the DiagrammeRsvg and rsvg packages must also be installed.
library(DiagrammeR)
gr <- xgb.plot.tree(model=bst, trees=0:1, render=FALSE)
export_graph(gr, 'tree.pdf', width=1500, height=1900)
export_graph(gr, 'tree.png', width=1500, height=1900)

## End(Not run)
```

---

xgb.save

*Save xgboost model to binary file*

---

## Description

Save xgboost model to a file in binary format.

## Usage

```
xgb.save(model, fname)
```

## Arguments

|       |                                    |
|-------|------------------------------------|
| model | model object of xgb.Booster class. |
| fname | name of the file to write.         |

## Details

This methods allows to save a model in an xgboost-internal binary format which is universal among the various xgboost interfaces. In R, the saved model file could be read-in later using either the [xgb.load](#) function or the xgb\_model parameter of [xgb.train](#).

Note: a model can also be saved as an R-object (e.g., by using [readRDS](#) or [save](#)). However, it would then only be compatible with R, and corresponding R-methods would need to be used to load it. Moreover, persisting the model with [readRDS](#) or [save](#) will cause compatibility problems in future versions of XGBoost. Consult [a-compatibility-note-for-saveRDS-save](#) to learn how to persist models in a future-proof way, i.e. to make the model accessible in future releases of XGBoost.

## See Also

[xgb.load](#), [xgb.Booster.complete](#).

## Examples

```
data(agaricus.train, package='xgboost')
data(agaricus.test, package='xgboost')
train <- agaricus.train
test <- agaricus.test
bst <- xgboost(data = train$data, label = train$label, max_depth = 2,
```

```

      eta = 1, nthread = 2, nrounds = 2, objective = "binary:logistic")
xgb.save(bst, 'xgb.model')
bst <- xgb.load('xgb.model')
if (file.exists('xgb.model')) file.remove('xgb.model')
pred <- predict(bst, test$data)

```

---

|              |  |
|--------------|--|
| xgb.save.raw | <i>Save xgboost model to R's raw vector; user can call xgb.load.raw to load the model back from raw vector</i> |
|--------------|--|

---

### Description

Save xgboost model from xgboost or xgb.train

### Usage

```
xgb.save.raw(model)
```

### Arguments

model            the model object.

### Examples

```

data(agaricus.train, package='xgboost')
data(agaricus.test, package='xgboost')
train <- agaricus.train
test <- agaricus.test
bst <- xgboost(data = train$data, label = train$label, max_depth = 2,
              eta = 1, nthread = 2, nrounds = 2, objective = "binary:logistic")
raw <- xgb.save.raw(bst)
bst <- xgb.load.raw(raw)
pred <- predict(bst, test$data)

```

---

|               |   |
|---------------|---|
| xgb.serialize | <i>Serialize the booster instance into R's raw vector. The serialization method differs from <a href="#">xgb.save.raw</a> as the latter one saves only the model but not parameters. This serialization format is not stable across different xgboost versions.</i> |
|---------------|---|

---

### Description

Serialize the booster instance into R's raw vector. The serialization method differs from [xgb.save.raw](#) as the latter one saves only the model but not parameters. This serialization format is not stable across different xgboost versions.

**Usage**

```
xgb.serialize(booster)
```

**Arguments**

booster            the booster instance

**Examples**

```
data(agaricus.train, package='xgboost')
data(agaricus.test, package='xgboost')
train <- agaricus.train
test <- agaricus.test
bst <- xgboost(data = train$data, label = train$label, max_depth = 2,
              eta = 1, nthread = 2, nrounds = 2, objective = "binary:logistic")
raw <- xgb.serialize(bst)
bst <- xgb.unserialize(raw)
```

---

xgb.set.config, xgb.get.config

*Set and get global configuration*

---

**Description**

Global configuration consists of a collection of parameters that can be applied in the global scope. See <https://xgboost.readthedocs.io/en/stable/parameter.html> for the full list of parameters supported in the global configuration. Use `xgb.set.config` to update the values of one or more global-scope parameters. Use `xgb.get.config` to fetch the current values of all global-scope parameters (listed in <https://xgboost.readthedocs.io/en/stable/parameter.html>).

**Usage**

```
xgb.set.config(...)
```

```
xgb.get.config()
```

**Arguments**

...                List of parameters to be set, as keyword arguments

**Value**

`xgb.set.config` returns TRUE to signal success. `xgb.get.config` returns a list containing all global-scope parameters and their values.

## Examples

```
# Set verbosity level to silent (0)
xgb.set.config(verbosity = 0)
# Now global verbosity level is 0
config <- xgb.get.config()
print(config$verbosity)
# Set verbosity level to warning (1)
xgb.set.config(verbosity = 1)
# Now global verbosity level is 1
config <- xgb.get.config()
print(config$verbosity)
```

---

xgb.train

*eXtreme Gradient Boosting Training*

---

## Description

xgb.train is an advanced interface for training an xgboost model. The xgboost function is a simpler wrapper for xgb.train.

## Usage

```
xgb.train(
  params = list(),
  data,
  nrounds,
  watchlist = list(),
  obj = NULL,
  feval = NULL,
  verbose = 1,
  print_every_n = 1L,
  early_stopping_rounds = NULL,
  maximize = NULL,
  save_period = NULL,
  save_name = "xgboost.model",
  xgb_model = NULL,
  callbacks = list(),
  ...
)

xgboost(
  data = NULL,
  label = NULL,
  missing = NA,
  weight = NULL,
  params = list(),
  nrounds,
```



```

    verbose = 1,
    print_every_n = 1L,
    early_stopping_rounds = NULL,
    maximize = NULL,
    save_period = NULL,
    save_name = "xgboost.model",
    xgb_model = NULL,
    callbacks = list(),
    ...
)

```

## Arguments

- params the list of parameters. The complete list of parameters is available in the [online documentation](#). Below is a shorter summary:
1. General Parameters
    - booster which booster to use, can be gbtree or gblinear. Default: gbtree.
  2. Booster Parameters
    - 2.1. Parameters for Tree Booster
      - eta control the learning rate: scale the contribution of each tree by a factor of  $0 < \eta < 1$  when it is added to the current approximation. Used to prevent overfitting by making the boosting process more conservative. Lower value for eta implies larger value for nrounds: low eta value means model more robust to overfitting but slower to compute. Default: 0.3
      - gamma minimum loss reduction required to make a further partition on a leaf node of the tree. the larger, the more conservative the algorithm will be.
      - max\_depth maximum depth of a tree. Default: 6
      - min\_child\_weight minimum sum of instance weight (hessian) needed in a child. If the tree partition step results in a leaf node with the sum of instance weight less than min\_child\_weight, then the building process will give up further partitioning. In linear regression mode, this simply corresponds to minimum number of instances needed to be in each node. The larger, the more conservative the algorithm will be. Default: 1
      - subsample subsample ratio of the training instance. Setting it to 0.5 means that xgboost randomly collected half of the data instances to grow trees and this will prevent overfitting. It makes computation shorter (because less data to analyse). It is advised to use this parameter with eta and increase nrounds. Default: 1
      - colsample\_bytree subsample ratio of columns when constructing each tree. Default: 1
      - lambda L2 regularization term on weights. Default: 1
      - alpha L1 regularization term on weights. (there is no L1 reg on bias because it is not important). Default: 0
      - num\_parallel\_tree Experimental parameter. number of trees to grow per round. Useful to test Random Forest through XGBoost (set colsample\_bytree < 1, subsample < 1 and round = 1) accordingly. Default: 1

- `monotone_constraints` A numerical vector consists of 1, 0 and -1 with its length equals to the number of features in the training data. 1 is increasing, -1 is decreasing and 0 is no constraint.
- `interaction_constraints` A list of vectors specifying feature indices of permitted interactions. Each item of the list represents one permitted interaction where specified features are allowed to interact with each other. Feature index values should start from 0 (0 references the first column). Leave argument unspecified for no interaction constraints.

## 2.2. Parameters for Linear Booster

- `lambda` L2 regularization term on weights. Default: 0
- `lambda_bias` L2 regularization term on bias. Default: 0
- `alpha` L1 regularization term on weights. (there is no L1 reg on bias because it is not important). Default: 0

## 3. Task Parameters

- `objective` specify the learning task and the corresponding learning objective, users can pass a self-defined function to it. The default objective options are below:
  - `reg:squarederror` Regression with squared loss (Default).
  - `reg:squaredlogerror`: regression with squared log loss  $1/2 * (\log(pred+1) - \log(label+1))^2$ . All inputs are required to be greater than -1. Also, see metric `rmsle` for possible issue with this objective.
  - `reg:logistic` logistic regression.
  - `reg:pseudohubererror`: regression with Pseudo Huber loss, a twice differentiable alternative to absolute loss.
  - `binary:logistic` logistic regression for binary classification. Output probability.
  - `binary:logitraw` logistic regression for binary classification, output score before logistic transformation.
  - `binary:hinge`: hinge loss for binary classification. This makes predictions of 0 or 1, rather than producing probabilities.
  - `count:poisson`: Poisson regression for count data, output mean of Poisson distribution. `max_delta_step` is set to 0.7 by default in poisson regression (used to safeguard optimization).
  - `survival:cox`: Cox regression for right censored survival time data (negative values are considered right censored). Note that predictions are returned on the hazard ratio scale (i.e., as  $HR = \exp(\text{marginal\_prediction})$ ) in the proportional hazard function  $h(t) = h_0(t) * HR$ .
  - `survival:aft`: Accelerated failure time model for censored survival time data. See [Survival Analysis with Accelerated Failure Time](#) for details.
  - `aft_loss_distribution`: Probability Density Function used by `survival:aft` and `aft-nloglik` metric.
  - `multi:softmax` set `xgboost` to do multiclass classification using the softmax objective. Class is represented by a number and should be from 0 to `num_class - 1`.

|                                    |   |
|------------------------------------|---|
|                                    | <ul style="list-style-type: none"> <li>– <code>multi:softprob</code> same as <code>softmax</code>, but prediction outputs a vector of <code>ndata * nclass</code> elements, which can be further reshaped to <code>ndata, nclass</code> matrix. The result contains predicted probabilities of each data point belonging to each class.</li> <li>– <code>rank:pairwise</code> set <code>xgboost</code> to do ranking task by minimizing the pairwise loss.</li> <li>– <code>rank:ndcg</code>: Use LambdaMART to perform list-wise ranking where <b>Normalized Discounted Cumulative Gain (NDCG)</b> is maximized.</li> <li>– <code>rank:map</code>: Use LambdaMART to perform list-wise ranking where <b>Mean Average Precision (MAP)</b> is maximized.</li> <li>– <code>reg:gamma</code>: gamma regression with log-link. Output is a mean of gamma distribution. It might be useful, e.g., for modeling insurance claims severity, or for any outcome that might be <b>gamma-distributed</b>.</li> <li>– <code>reg:tweedie</code>: Tweedie regression with log-link. It might be useful, e.g., for modeling total loss in insurance, or for any outcome that might be <b>Tweedie-distributed</b>.</li> <li>• <code>base_score</code> the initial prediction score of all instances, global bias. Default: 0.5</li> <li>• <code>eval_metric</code> evaluation metrics for validation data. Users can pass a self-defined function to it. Default: metric will be assigned according to objective (rmse for regression, and error for classification, mean average precision for ranking). List is provided in detail section.</li> </ul> |
| <code>data</code>                  | training dataset. <code>xgb.train</code> accepts only an <code>xgb.DMatrix</code> as the input. <code>xgboost</code> , in addition, also accepts <code>matrix</code> , <code>dgCMatrix</code> , or name of a local data file.   |
| <code>nrounds</code>               | max number of boosting iterations.  |
| <code>watchlist</code>             | named list of <code>xgb.DMatrix</code> datasets to use for evaluating model performance. Metrics specified in either <code>eval_metric</code> or <code>feval</code> will be computed for each of these datasets during each boosting iteration, and stored in the end as a field named <code>evaluation_log</code> in the resulting object. When either <code>verbose&gt;=1</code> or <code>cb.print.evaluation</code> callback is engaged, the performance results are continuously printed out during the training. E.g., specifying <code>watchlist=list(validation1=mat1, validation2=mat2)</code> allows to track the performance of each round's model on <code>mat1</code> and <code>mat2</code> .   |
| <code>obj</code>                   | customized objective function. Returns gradient and second order gradient with given prediction and <code>dtrain</code> .   |
| <code>feval</code>                 | customized evaluation function. Returns <code>list(metric='metric-name', value='metric-value')</code> with given prediction and <code>dtrain</code> .   |
| <code>verbose</code>               | If 0, <code>xgboost</code> will stay silent. If 1, it will print information about performance. If 2, some additional information will be printed out. Note that setting <code>verbose &gt; 0</code> automatically engages the <code>cb.print.evaluation(period=1)</code> callback function.  |
| <code>print_every_n</code>         | Print each n-th iteration evaluation messages when <code>verbose&gt;0</code> . Default is 1 which means all messages are printed. This parameter is passed to the <code>cb.print.evaluation</code> callback.  |
| <code>early_stopping_rounds</code> | If NULL, the early stopping function is not triggered. If set to an integer <code>k</code> , training with a validation set will stop if the performance doesn't improve for <code>k</code> rounds. Setting this parameter engages the <code>cb.early.stop</code> callback.   |

|             |   |
|-------------|---|
| maximize    | If feval and early_stopping_rounds are set, then this parameter must be set as well. When it is TRUE, it means the larger the evaluation score the better. This parameter is passed to the <code>cb.early.stop</code> callback.   |
| save_period | when it is non-NULL, model is saved to disk after every save_period rounds, 0 means save at the end. The saving is handled by the <code>cb.save.model</code> callback.  |
| save_name   | the name or path for periodically saved model file.   |
| xgb_model   | a previously built model to continue the training from. Could be either an object of class <code>xgb.Booster</code> , or its raw data, or the name of a file with a previously saved model.   |
| callbacks   | a list of callback functions to perform various task during boosting. See <a href="#">callbacks</a> . Some of the callbacks are automatically created depending on the parameters' values. User can provide either existing or their own callback methods in order to customize the training process. |
| ...         | other parameters to pass to <code>params</code> .   |
| label       | vector of response values. Should not be provided when data is a local data file name or an <code>xgb.DMatrix</code> .  |
| missing     | by default is set to NA, which means that NA values should be considered as 'missing' by the algorithm. Sometimes, 0 or other extreme value might be used to represent missing values. This parameter is only used when input is a dense matrix.  |
| weight      | a vector indicating the weight for each row of the input.   |

## Details

These are the training functions for `xgboost`.

The `xgb.train` interface supports advanced features such as `watchlist`, customized objective and evaluation metric functions, therefore it is more flexible than the `xgboost` interface.

Parallelization is automatically enabled if OpenMP is present. Number of threads can also be manually specified via `nthread` parameter.

The evaluation metric is chosen automatically by XGBoost (according to the objective) when the `eval_metric` parameter is not provided. User may set one or several `eval_metric` parameters. Note that when using a customized metric, only this single metric can be used. The following is the list of built-in metrics for which XGBoost provides optimized implementation:

- `rmse` root mean square error. [https://en.wikipedia.org/wiki/Root\\_mean\\_square\\_error](https://en.wikipedia.org/wiki/Root_mean_square_error)
- `logloss` negative log-likelihood. <https://en.wikipedia.org/wiki/Log-likelihood>
- `mlogloss` multiclass logloss. [https://scikit-learn.org/stable/modules/generated/sklearn.metrics.log\\_loss.html](https://scikit-learn.org/stable/modules/generated/sklearn.metrics.log_loss.html)
- `error` Binary classification error rate. It is calculated as  $(\# \text{ wrong cases}) / (\# \text{ all cases})$ . By default, it uses the 0.5 threshold for predicted values to define negative and positive instances. Different threshold (e.g., 0.) could be specified as "error@0."
- `merror` Multiclass classification error rate. It is calculated as  $(\# \text{ wrong cases}) / (\# \text{ all cases})$ .
- `mae` Mean absolute error

- `mape` Mean absolute percentage error
- `auc` Area under the curve. [https://en.wikipedia.org/wiki/Receiver\\_operating\\_characteristic#Area\\_under\\_curve](https://en.wikipedia.org/wiki/Receiver_operating_characteristic#Area_under_curve) for ranking evaluation.
- `aucpr` Area under the PR curve. [https://en.wikipedia.org/wiki/Precision\\_and\\_recall](https://en.wikipedia.org/wiki/Precision_and_recall) for ranking evaluation.
- `ndcg` Normalized Discounted Cumulative Gain (for ranking task). <https://en.wikipedia.org/wiki/NDCG>

The following callbacks are automatically created when certain parameters are set:

- `cb.print.evaluation` is turned on when `verbose > 0`; and the `print_every_n` parameter is passed to it.
- `cb.evaluation.log` is on when `watchlist` is present.
- `cb.early.stop`: when `early_stopping_rounds` is set.
- `cb.save.model`: when `save_period > 0` is set.

## Value

An object of class `xgb.Booster` with the following elements:

- `handle` a handle (pointer) to the xgboost model in memory.
- `raw` a cached memory dump of the xgboost model saved as R's raw type.
- `niter` number of boosting iterations.
- `evaluation_log` evaluation history stored as a `data.table` with the first column corresponding to iteration number and the rest corresponding to evaluation metrics' values. It is created by the `cb.evaluation.log` callback.
- `call` a function call.
- `params` parameters that were passed to the xgboost library. Note that it does not capture parameters changed by the `cb.reset.parameters` callback.
- `callbacks` callback functions that were either automatically assigned or explicitly passed.
- `best_iteration` iteration number with the best evaluation metric value (only available with early stopping).
- `best_score` the best evaluation metric value during early stopping. (only available with early stopping).
- `feature_names` names of the training dataset features (only when column names were defined in training data).
- `nfeatures` number of features in training data.

## References

Tianqi Chen and Carlos Guestrin, "XGBoost: A Scalable Tree Boosting System", 22nd SIGKDD Conference on Knowledge Discovery and Data Mining, 2016, <https://arxiv.org/abs/1603.02754>

**See Also**

[callbacks](#), [predict.xgb.Booster](#), [xgb.cv](#)

**Examples**

```

data(agaricus.train, package='xgboost')
data(agaricus.test, package='xgboost')

dtrain <- with(agaricus.train, xgb.DMatrix(data, label = label))
dtest <- with(agaricus.test, xgb.DMatrix(data, label = label))
watchlist <- list(train = dtrain, eval = dtest)

## A simple xgb.train example:
param <- list(max_depth = 2, eta = 1, verbose = 0, nthread = 2,
              objective = "binary:logistic", eval_metric = "auc")
bst <- xgb.train(param, dtrain, nrounds = 2, watchlist)

## An xgb.train example where custom objective and evaluation metric are used:
logregobj <- function(preds, dtrain) {
  labels <- getinfo(dtrain, "label")
  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")
  err <- as.numeric(sum(labels != (preds > 0)))/length(labels)
  return(list(metric = "error", value = err))
}

# These functions could be used by passing them either:
# as 'objective' and 'eval_metric' parameters in the params list:
param <- list(max_depth = 2, eta = 1, verbose = 0, nthread = 2,
              objective = logregobj, eval_metric = evalerror)
bst <- xgb.train(param, dtrain, nrounds = 2, watchlist)

# or through the ... arguments:
param <- list(max_depth = 2, eta = 1, verbose = 0, nthread = 2)
bst <- xgb.train(param, dtrain, nrounds = 2, watchlist,
                 objective = logregobj, eval_metric = evalerror)

# or as dedicated 'obj' and 'feval' parameters of xgb.train:
bst <- xgb.train(param, dtrain, nrounds = 2, watchlist,
                 obj = logregobj, feval = evalerror)

## An xgb.train example of using variable learning rates at each iteration:
param <- list(max_depth = 2, eta = 1, verbose = 0, nthread = 2,
              objective = "binary:logistic", eval_metric = "auc")
my_etas <- list(eta = c(0.5, 0.1))

```

```

bst <- xgb.train(param, dtrain, nrounds = 2, watchlist,
                callbacks = list(cb.reset.parameters(my_etas)))

## Early stopping:
bst <- xgb.train(param, dtrain, nrounds = 25, watchlist,
                early_stopping_rounds = 3)

## An 'xgboost' interface example:
bst <- xgboost(data = agaricus.train$data, label = agaricus.train$label,
               max_depth = 2, eta = 1, nthread = 2, nrounds = 2,
               objective = "binary:logistic")
pred <- predict(bst, agaricus.test$data)

```

---

xgb.unserialize      *Load the instance back from [xgb.serialize](#)*

---

### Description

Load the instance back from [xgb.serialize](#)

### Usage

```
xgb.unserialize(buffer, handle = NULL)
```

### Arguments

|        |   |
|--------|---|
| buffer | the buffer containing booster instance saved by <a href="#">xgb.serialize</a>   |
| handle | An <code>xgb.Booster.handle</code> object which will be overwritten with the new deserialized object. Must be a null handle (e.g. when loading the model through <code>'readRDS'</code> ). If not provided, a new handle will be created. |

### Value

An `xgb.Booster.handle` object.

---

xgboost-deprecated      *Deprecation notices.*

---

### Description

At this time, some of the parameter names were changed in order to make the code style more uniform. The deprecated parameters would be removed in the next release.

**Details**

To see all the current deprecated and new parameters, check the `xgboost:::depr_par_lut` table.

A deprecation warning is shown when any of the deprecated parameters is used in a call. An additional warning is shown when there was a partial match to a deprecated parameter (as R is able to partially match parameter names).



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