

Package ‘superml’

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Type Package

Title Build Machine Learning Models Like Using Python's Scikit-Learn Library in R

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Description The idea is to provide a standard interface to users who use both R and Python for building machine learning models. This package provides a scikit-learn's fit, predict interface to train machine learning models in R.

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BugReports <https://github.com/saraswatmks/superml/issues>

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R topics documented:

bm25	2
cla_train	3
Counter	4
CountVectorizer	4
GridSearchCV	5
kFoldMean	6
KMeansTrainer	7
KNNTrainer	8
LabelEncoder	9
LMTrainer	10
NBTrainer	12
RandomSearchCV	13
reg_train	14
RFTrainer	14
smoothMean	16
SVMTrainer	17
TfidfVectorizer	18
XGBTrainer	19

Index	22
--------------	-----------

bm25	<i>Best Matching(BM25)</i>
------	----------------------------

Description

BM25 stands for Best Matching 25. It is widely using for ranking documents and a preferred method than TF*IDF scores. It is used to find the similar documents from a corpus, given a new document. It is popularly used in information retrieval systems. This implementation uses multiple cores for faster and parallel computation.

Usage

```
bm25
```

Format

[R6Class](#) object.

Usage

For usage details see **Methods, Arguments and Examples** sections.

```
bm25 = bm25$new(corpus, n_cores)
bm25$most_similar(input_document, topn)
bm25$compute(input_document)
```

Methods

`$new()` Initialise the instance of the class. Here you pass the complete corpus of the documents

`$most_similar()` it returns the topn most similar documents from the corpus

`$compute()` it returns a similarity score for all the documents in the corpus, given a sentence

Arguments

corpus a list containing sentences

use_parallel boolean value used to activate parallel computation, defaults to FALSE

Examples

```
example <- c('white audi 2.5 car', 'black shoes from office',
            'new mobile iphone 7', 'audi tyres audi a3',
            'nice audi bmw toyota corolla')
get_bm <- bm25$new(example, use_parallel=FALSE)
input_document <- c('white toyota corolla')
get_bm$most_similar(document = input_document, topn = 2)
```

 cla_train

cla_train

Description

Training Dataset used for classification examples. This is classic titanic dataset used to predict if a passenger will survive or not in titanic ship disaster.

Usage

```
cla_train
```

Format

A data frame with 12 variables:

PassengerId unique ID of the passenger

Survived survival of the passenger

Pclass ticket class

Name name of the passenger

Sex sex of the passenger

Age Age of the passenger

SibSp number of siblings/spouse aboard the titanic

Parch number of parents / child aboard the titanic

Ticket ticket number

Fare passenger fare

Cabin cabin number

Embarked port of embarkation

Source

<https://www.kaggle.com/c/titanic/data>

Counter	<i>Calculate count of values in a list or vector</i>
---------	--

Description

Handy function to calculate count of values given in a list or vector

Usage

```
Counter(data, sort = TRUE, decreasing = FALSE)
```

Arguments

data	should be a vector or list of input values
sort	a logical value, to sort the result or not
decreasing	a logical value, the order of sorting to be followed

Value

count of values in a list

Examples

```
d <- list(c('i', 'am', 'bad'), c('you', 'are', 'also', 'bad'))
counts <- Counter(d, sort=TRUE, decreasing=TRUE)
```

CountVectorizer	<i>Count Vectorizer</i>
-----------------	-------------------------

Description

Creates CountVectorizer Model. Given a list of text, it generates a bag of words model and returns a data frame consisting of BOW features.

Usage

```
CountVectorizer
```

Format

[R6Class](#) object.

Usage

For usage details see **Methods, Arguments and Examples** sections.

```
bst = CountVectorizer$new(min_df=1, max_df=1, max_features=1)
bst$fit(sentences)
bst$fit_transform(sentences)
bst$transform(sentences)
```

Methods

`$new()` Initialise the instance of the vectorizer
`$fit()` creates a memory of bag of words
`$transform()` based on encodings learned in fit method, return a bag of words matrix
`$fit_transform()` simultaneously fits and transform words and returns bag of words of matrix

Examples

```
df <- data.frame(sents = c('i am alone in dark.', 'mother_mary a lot',
                          'alone in the dark?',
                          'many mothers in the lot...'))

# fits and transforms on the entire data in one go
bw <- CountVectorizer$new(min_df = 0.3)
tf_features <- bw$fit_transform(df$sents)

# fit on entire data and do transformation in train and test
bw <- CountVectorizer$new()
bw$fit(df$sents)
tf_features <- bw$transform(df$sents)
```

GridSearchCV

Grid Search CV

Description

Grid search CV is used to train a machine learning model with multiple combinations of training hyper parameters and finds the best combination of parameters which optimizes the evaluation metric. It creates an exhaustive set of hyperparameter combinations and train model on each combination.

Usage

```
GridSearchCV
```

Format

[R6Class](#) object.

Usage

For usage details see **Methods, Arguments and Examples** sections.

```
gst = GridSearchTrainer$new(trainer, parameters, n_folds, scoring)
gst$fit(X, y)
gst$best_iteration(metric)
```

Methods

`$new()` Initialises an instance of grid search cv

`$fit()` fit model to an input train data and trains the model.

`$best_iteration()` returns best iteration based on a given metric. By default, uses the first scoring metric

Arguments

trainer superml trainer object, could be either XGBTrainer, RFTrainer, NBTrainer etc.

parameters list containing parameters

n_folds number of folds to use to split the train data

scoring scoring metric used to evaluate the best model, multiple values can be provided. currently supports: auc, accuracy, mse, rmse, logloss, mae, f1, precision, recall

Examples

```
rf <- RFTrainer$new()
gst <- GridSearchCV$new(trainer = rf,
                       parameters = list(n_estimators = c(100),
                                         max_depth = c(5,2,10)),
                       n_folds = 3,
                       scoring = c('accuracy', 'auc'))

data("iris")
gst$fit(iris, "Species")
gst$best_iteration()
```

kFoldMean

kFoldMean Calculator

Description

Calculates out-of-fold mean features (also known as target encoding) for train and test data. This strategy is widely used to avoid overfitting or causing leakage while creating features using the target variable. This method is experimental. If the results you get are unexpected, please report them in github issues.

Usage

```
kFoldMean(train_df, test_df, colname, target, n_fold = 5, seed = 42)
```

Arguments

train_df	train dataset
test_df	test dataset
colname	name of categorical column
target	the target or dependent variable, should be a string.
n_fold	the number of folds to use for doing kfold computation, default=5
seed	the seed value, to ensure reproducibility, it could be any positive value, default=42

Value

a train and test data table with out-of-fold mean value of the target for the given categorical variable

Examples

```
train <- data.frame(region=c('del', 'csk', 'rcb', 'del', 'csk', 'pune', 'guj', 'del'),
                    win = c(0,1,1,0,0,0,0,1))
test <- data.frame(region=c('rcb', 'csk', 'rcb', 'del', 'guj', 'pune', 'csk', 'kol'))
train_result <- kFoldMean(train_df = train,
                          test_df = test,
                          colname = 'region',
                          target = 'win',
                          seed = 1220)$train

test_result <- kFoldMean(train_df = train,
                         test_df = test,
                         colname = 'region',
                         target = 'win',
                         seed = 1220)$test
```

KMeansTrainer

K-Means Trainer

Description

Trains a unsupervised K-Means clustering algorithm. It borrows mini-batch k-means function from ClusterR package written in c++, hence it is quite fast.

Usage

```
KMeansTrainer
```

Format

[R6Class](#) object.

Usage

For usage details see **Methods, Arguments and Examples** sections.

```
kmt = KMeansTrainer$new(clusters, batch_size = 10, num_init=1, max_iters=100,
  init_fraction=1, initializer = "kmeans++", early_stop_iter = 10,
  verbose=FALSE, centroids=NULL, tol = 1e-04, tol_optimal_init=0.3,
  seed=1, max_clusters=NA)
bst$fit(X_train, y_train=NULL)
prediction <- bst$predict(X_test)
```

Methods

`$new()` Initialises an instance of k-means model
`$fit()` fit model to an input train data
`$predict()` returns cluster predictions for each row of given data

Arguments

params for explanation on parameters, please refer to the documentation of MiniBatchKMeans function in clusterR package <https://CRAN.R-project.org/package=ClusterR>

find_optimal Used to find the optimal number of cluster during fit method. To use this, make sure the value for max_clusters > 0.

Examples

```
data <- rbind(replicate(20, rnorm(1e4, 2)),
  replicate(20, rnorm(1e4, -1)),
  replicate(20, rnorm(1e4, 5)))
km_model <- KMeansTrainer$new(clusters=2, batch_size=30, max_clusters=6)
km_model$fit(data, find_optimal = FALSE)
predictions <- km_model$predict(data)
```

 KNNTrainer

K Nearest Neighbours Trainer

Description

Trains a k nearest neighbour model using fast search algorithms. KNN is a supervised learning algorithm which is used for both regression and classification problems.

Usage

```
KNNTrainer
```

Format

[R6Class](#) object.

Usage

For usage details see **Methods, Arguments and Examples** sections.

```
bst = KNNTrainer$new(k=1, prob=FALSE, algorithm=NULL, type="class")
bst$fit(X_train, X_test, "target")
bst$predict(type)
```

Methods

`$new()` Initialise the instance of the trainer
`$fit()` trains the knn model and stores the test prediction
`$predict()` returns predictions

Arguments

k number of neighbours to predict
prob if probability should be computed, default=FALSE
algorithm algorithm used to train the model, possible values are 'kd_tree', 'cover_tree', 'brute'
type type of problem to solve i.e. regression or classification, possible values are 'reg' or 'class'

Examples

```
data("iris")

iris$Species <- as.integer(as.factor(iris$Species))

xtrain <- iris[1:100,]
xtest <- iris[101:150,]

bst <- KNNTrainer$new(k=3, prob=TRUE, type="class")
bst$fit(xtrain, xtest, 'Species')
pred <- bst$predict(type="raw")
```

LabelEncoder

Label Encoder

Description

Encodes and decodes categorical variables into integer values and vice versa. This is a commonly performed task in data preparation during model training, because all machine learning models require the data to be encoded into numerical format. It takes a vector of character or factor values and encodes them into numeric.

Usage

LabelEncoder

Format

R6Class object.

Usage

For usage details see **Methods, Arguments and Examples** sections.

```
lbl = LabelEncoder$new()  
lbl$fit(x)  
lbl$fit_transform(x)  
lbl$transform(x)
```

Methods

`$new()` Initialise the instance of the encoder
`$fit()` creates a memory of encodings but doesn't return anything
`$transform()` based on encodings learned in `fit` method is applies the transformation
`$fit_transform()` encodes the data and keep a memory of encodings simultaneously
`$inverse_transform()` encodes the data and keep a memory of encodings simultaneously

Arguments

data a vector or list containing the character / factor values

Examples

```
data_ex <- data.frame(Score = c(10,20,30,4), Name=c('Ao', 'Bo', 'Bo', 'Co'))  
lbl <- LabelEncoder$new()  
data_ex$Name <- lbl$fit_transform(data_ex$Name)  
decode_names <- lbl$inverse_transform(data_ex$Name)
```

LMTrainer

Linear Models Trainer

Description

Trains linear models such as Logistic, Lasso or Ridge regression model. It is built on glmnet R package. This class provides fit, predict, cross validation functions.

Usage

LMTrainer

Format

R6Class object.

Usage

For usage details see **Methods, Arguments and Examples** sections.

```
bst = LMTrainer$new(family, weights, alpha, lambda=100, standardize.response=FALSE)
bst$fit(X_train, "target")
prediction <- bst$predict(X_test)
bst$cv_model(X_train, "target", nfolds=4, parallel=TRUE)
cv_prediction <- bst$cv_predict(X_test)
```

Methods

`$new()` Initialises an instance of random forest model

`$fit()` fit model to an input train data (data frame or data table) and trains the model.

`$predict()` returns predictions by fitting the trained model on test data.

`$cv_model()` Using k-fold cross validation technique, finds the best value of lambda. type.measure is the loss to use for cross validation.

`$cv_predict()` Using the best value of lambda, makes predictions on the test data

`$get_importance()` Returns a matrix of feature coefficients as generated by Lasso

Arguments

family type of regression to perform, values can be "gaussian", "binomial", "multinomial", "mgaussian"

weights observation weights. Can be total counts if responses are proportion matrices. Default is 1 for each observation

alpha The elasticnet mixing parameter, alpha=1 is the lasso penalty, and alpha=0 the ridge penalty.

nlambda the number of lambda values - default is 100

standardize.response normalise the dependent variable between 0 and 1, default = FALSE

Examples

```
LINK <- "http://archive.ics.uci.edu/ml/machine-learning-databases/housing/housing.data"
housing <- read.table(LINK)
names <- c("CRIM", "ZN", "INDUS", "CHAS", "NOX", "RM", "AGE", "DIS",
          "RAD", "TAX", "PTRATIO", "B", "LSTAT", "MEDV")
names(housing) <- names
lf <- LMTrainer$new(family = 'gaussian', alpha=1)
lf$fit(X = housing, y = 'MEDV')
predictions <- lf$predict(df = housing)

# cross validation model
lf$cv_model(X = housing, y = 'MEDV', nfolds = 5, parallel = FALSE)
predictions <- lf$cv_predict(df = housing)
coefs <- lf$get_importance()
```

NBTrainer*Naive Bayes Trainer*

Description

Trains a naive bayes model. It is built on top high performance naivebayes R package.

Usage

```
NBTrainer
```

Format

[R6Class](#) object.

Usage

For usage details see **Methods, Arguments and Examples** sections.

```
nbt = NBTrainer$new(prior=NULL, laplace=0, usekernel=FALSE)
nbt$fit(X_train, "target")
prediction <- nbt$predict(X_test)
```

Methods

`$new()` Initialises an instance of naive bayes model

`$fit()` fits model to an input train data and trains the model.

`$predict()` returns predictions by fitting the trained model on test data.

Arguments

prior for detailed explanation of parameters, check: <https://cran.r-project.org/package=naivebayes>

prior numeric vector with prior probabilities. vector with prior probabilities of the classes. If unspecified, the class proportions for the training set are used. If present, the probabilities should be specified in the order of the factor levels.

laplace value used for Laplace smoothing. Defaults to 0 (no Laplace smoothing)

usekernel if TRUE, density is used to estimate the densities of metric predictors

Examples

```
data(iris)
nb <- NBTrainer$new()
nb$fit(iris, 'Species')
y <- nb$predict(iris)
```

RandomSearchCV

Random Search CV

Description

Given a set of hyper parameters, random search trainer provides a faster way of hyper parameter tuning. Here, the number of models to be trained can be defined by the user.

Usage

```
RandomSearchCV
```

Format

[R6Class](#) object.

Usage

For usage details see **Methods, Arguments and Examples** sections.

```
rst = RandomSearchCV$new(trainer, parameters, n_folds, scoring, n_iter)
rst$fit(X_train, "target")
rst$best_iteration(metric)
```

Methods

`$new()` Initialises an instance of random search cv

`$fit()` fit model to an input train data and trains the model.

`$best_iteration()` returns best iteration based on a given metric. By default, uses the first scoring metric

Arguments

trainer superml trainer object, must be either XGBTrainer, LMTrainer, RFTrainer, NBTrainer

parameters list containing parameters

n_folds number of folds to use to split the train data

scoring scoring metric used to evaluate the best model, multiple values can be provided. currently supports: auc, accuracy, mse, rmse, logloss, mae, f1, precision, recall

n_iter number of models to be trained

Examples

```
rf <- RFTrainer$new()
rst <- RandomSearchCV$new(trainer = rf,
                          parameters = list(n_estimators = c(100,500),
                                             max_depth = c(5,2,10,14)),
                          n_folds = 3,
                          scoring = c('accuracy','auc'),
                          n_iter = 4)

data("iris")
rst$fit(iris, "Species")
rst$best_iteration()
```

reg_train	<i>reg_train</i>
-----------	------------------

Description

Training Dataset used for regression examples. In this data set, we have to predict the sale price of the houses.

Usage

```
reg_train
```

Format

An object of class `data.table` (inherits from `data.frame`) with 1460 rows and 81 columns.

RFTrainer	<i>Random Forest Trainer</i>
-----------	------------------------------

Description

Trains a Random Forest model. A random forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and use averaging to improve the predictive accuracy and control over-fitting. This implementation uses ranger R package which provides faster model training.

Usage

```
RFTrainer
```

Format

[R6Class](#) object.

Usage

For usage details see **Methods, Arguments and Examples** sections.

```
bst = RFTrainer$new(n_estimators=100, max_features="auto", max_depth=5, min_node_size=1,
                   criterion, classification=1, class_weights, verbose=TRUE,
                   seed=42, always_split)
bst$fit(X_train, "target")
prediction <- bst$predict(X_test)
```

Methods

`$new()` Initialises an instance of random forest model
`$fit()` fit model to an input train data and trains the model.
`$predict()` returns predictions by fitting the trained model on test data.
`$get_importance()` Get feature importance from the model

Arguments

n_estimators the number of trees in the forest, default= 100
max_features the number of features to consider when looking for the best split. Possible values are auto(default) takes sqrt(num_of_features), sqrt same as auto, log takes log(num_of_features), none takes all features
max_depth the maximum depth of each tree
min_node_size the minimum number of samples required to split an internal node
criterion the function to measure the quality of split. For classification, gini is used which is a measure of gini index. For regression, the variance of responses is used.
classification whether to train for classification (1) or regression (0)
class_weights weights associated with the classes for sampling of training observation
verbose show computation status and estimated runtime
always_split vector of feature names to be always used for splitting
seed seed value
importance Variable importance mode, one of 'none', 'impurity', 'impurity_corrected', 'permutation'. The 'impurity' measure is the Gini index for classification, the variance of the responses for regression. Defaults to "impurity"

Examples

```
data("iris")
bst <- RFTrainer$new(n_estimators=50,
                    max_depth=4,
                    classification=1,
                    seed=42,
                    verbose=TRUE)
bst$fit(iris, 'Species')
predictions <- bst$predict(iris)
bst$get_importance()
```

`smoothMean`*smoothMean Calculator*

Description

Calculates target encodings using a smoothing parameter and count of categorical variables. This approach is more robust to possibility of leakage and avoid overfitting.

Usage

```
smoothMean(train_df, test_df, colname, target, min_samples_leaf = 1,  
           smoothing = 1, noise_level = 0)
```

Arguments

<code>train_df</code>	train dataset
<code>test_df</code>	test dataset
<code>colname</code>	name of categorical column
<code>target</code>	name of target column
<code>min_samples_leaf</code>	minimum samples to take category average into account
<code>smoothing</code>	smoothing effect to balance categorical average vs prior
<code>noise_level</code>	random noise to add, optional

Value

a train and test data table with mean encodings of the target for the given categorical variable

Examples

```
train <- data.frame(region=c('del', 'csk', 'rcb', 'del', 'csk', 'pune', 'guj', 'del'),  
                   win = c(0,1,1,0,0,1,0,1))  
test <- data.frame(region=c('rcb', 'csk', 'rcb', 'del', 'guj', 'pune', 'csk', 'kol'))  
  
# calculate encodings  
all_means <- smoothMean(train_df = train,  
                       test_df = test,  
                       colname = 'region',  
                       target = 'win')  
train_mean <- all_means$train  
test_mean <- all_means$test
```

SVMTrainer

Support Vector Machines Trainer

Description

Trains a support vector machine (svm) model. It is based on the magnificently fast speed liquidSVM R package. It provides a more unified interface over the package retaining all its functionality.

The model is intelligently trained with a default set of hyper parameters. Also, there are inbuilt grid setups which can be easily initialised. It has capability to support batch processing of data to avoid memory errors. It supports binary classification, multi classification, regression models

Usage

SVMTrainer

Format

R6Class object.

Usage

For usage details see **Methods, Arguments and Examples** sections.

```
svm = SVMTrainer$new(type=NULL, scale=TRUE, gammas=NULL, lambdas=NULL, c_values=NULL,
                    predict.prob=FALSE, verbose=NULL, ncores=NULL, partition_choice=0,
                    seed=-1, grid_choice=NULL, useCells=FALSE, mc_type=NULL,
                    adaptivity_control=0)
svm$fit(X_train, y_train)
prediction <- svm$predict(X_test)
```

Methods

`$new()` Initialises an instance of svm model

`$fit()` fits model to an input train data and trains the model.

`$predict()` returns predictions by fitting the trained model on test data.

Arguments

params for detailed explanation on parameters, refer to original documentation <https://cran.r-project.org/web/packages/e1071>

type type of model to train, possible values: "bc" = binary classification, "mc" = multiclassification, "ls" = least square regression, "qt" = quantile regression

scale normalises the feature between 0 and 1, default = TRUE

gammas bandwidth of the kernel, default value is chosen from a list of gamma values generated internally

Examples

```
data(iris)
## Multiclassification
svm <- SVMTrainer$new()
svm$fit(iris, "Species")
p <- svm$predict(iris)

## Least Squares
svm <- SVMTrainer$new()
svm$fit(trees, "Height")
p <- svm$predict(trees)
```

TfIdfVectorizer

TfIDF(Term Frequency Inverse Document Frequency) Vectorizer

Description

Provides an easy way to create tf-idf matrix of features in R. It consists of fit, transform methods (similar to sklearn) to generate tf-idf features.

Usage

```
TfIdfVectorizer
```

Format

[R6Class](#) object.

Usage

For usage details see **Methods, Arguments and Examples** sections.

```
tf_object = TfIdfVectorizer$new(max_df=1, min_df=1, max_features=1, smooth_idf=TRUE)
tf_object$fit(sentences)
tf_matrix = tf_object$transform(sentences)
tf_matrix = tf_object$fit_transform(sentences) ## alternate
```

Methods

`$new()` Initialise the instance of the vectorizer
`$fit()` creates a memory of count vectorizers but doesn't return anything
`$transform()` based on encodings learned in fit method, returns the tf-idf matrix
`$fit_transform()` returns tf-idf matrix

Examples

```
df <- data.frame(sents = c('i am alone in dark.',
                           'mother_mary a lot',
                           'alone in the dark?',
                           'many mothers in the lot...'))
tf <- TfIdfVectorizer$new(smooth_idf = TRUE, min_df = 0.3)
tf_features <- tf$fit_transform(df$sents)
```

XGBTrainer

*Extreme Gradient Boosting Trainer***Description**

Trains a Extreme Gradient Boosting Model. XGBoost belongs to a family of boosting algorithms that creates an ensemble of weak learner to learn about data.

Usage

```
XGBTrainer
```

Format

[R6Class](#) object.

Usage

For usage details see **Methods, Arguments and Examples** sections.

```
bst = XGBTrainer$new(booster, objective, nthread, silent=0, n_estimators=100,
                    learning_rate=0.3, gamma=0, max_depth=6, min_child_weight=1,
                    subsample=1, colsample_bytree=1, lambda=1, alpha = 0,
                    eval_metric, print_every = 50, feval, early_stopping,
                    maximize, custom_objective, save_period, save_name,
                    xgb_model, callbacks, verbose, num_class, weight, na_missing)
bst$fit(X_train, "target", valid=NULL)
tfidf$predict(X_test)
```

Methods

- `$new()` Initialises an instance of xgboost model
- `$fit()` fits model to an input train data using given parametes.
- `$cross_val()` performs cross validation on train data
- `$predict()` returns predictions by fitting the trained model on test data.

Arguments

params the detailed version of these arguments can found in xgboost documentation <http://xgboost.readthedocs.io/en/latest/parameter.html>

booster the trainer type, the values are gbtree(default), gblinear, dart:gbtree

objective specify the learning task. Check the link above for all possible values.

max_features the number of features to consider when looking for the best split Possible values are auto,sqrt,log,None

n_thread number of parallel threads used to run, default is to run using all threads available

silent 0 means printing running messages, 1 means silent mode

n_estimators number of trees to grow, default = 100

learning_rate Step size shrinkage used in update to prevents overfitting. Lower the learning rate, more time it takes in training, value lies between between 0 and 1. Default = 0.3

max_depth the maximum depth of each tree, default = 6

nfold set number of folds for cross validation

stratified if stratified sampling to be done or not, default is TRUE

folds the list of CV folds' indices - either those passed through the folds parameter or randomly generated.

gamma Minimum loss reduction required to make a further partition on a leaf node of the tree. The larger gamma is, the more conservative the algorithm will be. Value lies between 0 and infinity, Default = 0

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 task, this simply corresponds to minimum number of instances needed to be in each node. The larger min_child_weight is, the more conservative the algorithm will be. Value lies between 0 and infinity. Default = 1

subsample Subsample ratio of the training instances. Setting it to 0.5 means that XGBoost would randomly sample half of the training data prior to growing trees. and this will prevent overfitting. Subsampling will occur once in every boosting iteration. Value lies between 0 and 1. Default = 1

colsample_bytree Subsample ratio of columns when constructing each tree. Subsampling will occur once in every boosting iteration. Value lies between 0 and 1. Default = 1

lambda L2 regularization term on weights. Increasing this value will make model more conservative. Default = 1

alpha L1 regularization term on weights. Increasing this value will make model more conservative. Default = 0

eval_metric Evaluation metrics for validation data, a default metric will be assigned according to objective

print_every print training log after n iterations. Default = 50

feval custom evaluation function

early_stopping Used to prevent overfitting, stops model training after this number of iterations if there is no improvement seen

- 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.
- custom_objective** custom objective function
- save_period** when it is non-NULL, model is saved to disk after every save_period rounds, 0 means save at the end.
- 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 xgb.Booster, 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 callbacks. 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.
- verbose** If 0, xgboost will stay silent. If 1, xgboost will print information of performance. If 2, xgboost will print some additional information. Setting verbose > 0 automatically engages the cb.evaluation.log and cb.print.evaluation callback functions.
- watchlist** what information should be printed when verbose=1 or verbose=2. Watchlist is used to specify validation set monitoring during training. For example user can specify watchlist=list(validation1=mat1, validation2=mat2) to watch the performance of each round's model on mat1 and mat2
- num_class** set number of classes in case of multiclassification problem
- weight** a vector indicating the weight for each row of the input.
- na_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.

Examples

```
library(data.table)
df <- copy(iris)

# convert characters/factors to numeric
df$Species <- as.numeric(as.factor(df$Species))-1

# initialise model
xgb <- XGBTrainer$new(objective = 'multi:softmax',
                      maximize = FALSE,
                      eval_metric = 'merror',
                      num_class=3,
                      n_estimators = 2)
xgb$fit(df, 'Species')

# do cross validation to find optimal value for n_estimators
xgb$cross_val(X = df, y = 'Species',nfolds = 3, stratified = TRUE,
             early_stopping = 1)
best_iter <- xgb$scv_model$best_iteration
xgb$show_importance()

# make predictions
preds <- xgb$predict(as.matrix(iris[,1:4]))
preds
```

Index

*Topic **datasets**

- bm25, [2](#)
 - cla_train, [3](#)
 - CountVectorizer, [4](#)
 - GridSearchCV, [5](#)
 - KMeansTrainer, [7](#)
 - KNNTrainer, [8](#)
 - LabelEncoder, [9](#)
 - LMTrainer, [10](#)
 - NBTrainer, [12](#)
 - RandomSearchCV, [13](#)
 - reg_train, [14](#)
 - RFTrainer, [14](#)
 - SVMTrainer, [17](#)
 - TfidfVectorizer, [18](#)
 - XGBTrainer, [19](#)
-
- bm25, [2](#)
 - cla_train, [3](#)
 - Counter, [4](#)
 - CountVectorizer, [4](#)
 - GridSearchCV, [5](#)
 - kFoldMean, [6](#)
 - KMeansTrainer, [7](#)
 - KNNTrainer, [8](#)
 - LabelEncoder, [9](#)
 - LMTrainer, [10](#)
 - NBTrainer, [12](#)
 - R6Class, [2](#), [4](#), [5](#), [7](#), [8](#), [10](#), [12–14](#), [17–19](#)
 - RandomSearchCV, [13](#)
 - reg_train, [14](#)
 - RFTrainer, [14](#)
 - smoothMean, [16](#)
 - SVMTrainer, [17](#)
 - TfidfVectorizer, [18](#)
 - XGBTrainer, [19](#)