Package ‘rsparse’

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Type Package
Title Statistical Learning on Sparse Matrices
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Description Implements many algorithms for statistical learning on sparse matrices - matrix factorizations, matrix completion, elastic net regressions, factorization machines. Also 'rsparse' enhances 'Matrix' package by providing methods for multithreaded <sparse, dense> matrix products and native slicing of the sparse matrices in Compressed Sparse Row (CSR) format. List of the algorithms for regression problems:
1) Elastic Net regression via Follow The Proximally-Regularized Leader (FTRL) Stochastic Gradient Descent (SGD), as per McMahan et al,(<doi:10.1145/2487575.2488200>)
2) Factorization Machines via SGD, as per Rendle (2010, <doi:10.1109/ICDM.2010.127>)
List of algorithms for matrix factorization and matrix completion:
5) GlobalVectors (GloVe) matrix factorization via SGD, paper by Pennington, Socher, Manning (2014, <https://www.aclweb.org/anthology/D14-1162>)
Package is reasonably fast and memory efficient - it allows to work with large datasets - millions of rows and millions of columns. This is particularly useful for practitioners working on recommender systems.

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**R topics documented:**

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**detect_number_omp_threads**

*Detects number of OpenMP threads in the system*

**Description**

Detects number of OpenMP threads in the system respecting environment variables such as `OMP_NUM_THREADS` and `OMP_THREAD_LIMIT`.

**Usage**

```r
detect_number_omp_threads()
```

---

**FactorizationMachine**  
*Second order Factorization Machines*

**Description**

Creates second order Factorization Machines model.

**Methods**

**Public methods:**

- `FactorizationMachine$new()`
- `FactorizationMachine$partial_fit()`
- `FactorizationMachine$fit()`
- `FactorizationMachine$predict()`
- `FactorizationMachine$clone()`

**Method** `new()`: creates second order Factorization Machines model

**Usage:**

```r
FactorizationMachine$new(
    learning_rate_w = 0.2,
    rank = 4,
    lambda_w = 0,
    lambda_v = 0,
    family = c("binomial", "gaussian"),
    intercept = TRUE,
    learning_rate_v = learning_rate_w
)
```

**Arguments:**

- `learning_rate_w` learning rate for features intercations
- `rank` dimension of the latent dimensions which models features interactions
lambda_w regularization for features interactions
lambda_v regularization for features
family one of "binomial", "gaussian"
intercept logical, indicates whether or not include intecept to the model
learning_rate_v learning rate for features

**Method** partial_fit(): fits/updates model

*Usage:*
FactorizationMachine$partial_fit(x, y, weights = rep(1, length(y)), ...)  

*Arguments:*
  x  input sparse matrix. Native format is Matrix::RsparseMatrix. If x is in different format,  
      model will try to convert it to RsparseMatrix with as(x, "RsparseMatrix"). Dimensions  
      should be (n_samples, n_features)
y  vector of targets
weights numeric vector of length 'n_samples'. Defines how to amplify SGD updates for each  
      sample. May be useful for highly unbalanced problems.
... not used at the moment

**Method** fit(): shorthand for applying 'partial_fit' 'n_iter' times

*Usage:*
FactorizationMachine$fit(x, y, weights = rep(1, length(y)), n_iter = 1L, ...)  

*Arguments:*
  x  input sparse matrix. Native format is Matrix::RsparseMatrix. If x is in different format,  
      model will try to convert it to RsparseMatrix with as(x, "RsparseMatrix"). Dimensions  
      should be (n_samples, n_features)
y  vector of targets
weights numeric vector of length 'n_samples'. Defines how to amplify SGD updates for each  
      sample. May be useful for highly unbalanced problems.
n_iter number of SGD epochs
... not used at the moment

**Method** predict(): makes predictions based on fitted model

*Usage:*
FactorizationMachine$predict(x, ...)  

*Arguments:*
  x  input sparse matrix of shape (n_samples, n_features)
... not used at the moment

**Method** clone(): The objects of this class are cloneable with this method.

*Usage:*
FactorizationMachine$clone(deep = FALSE)  

*Arguments:*
deep Whether to make a deep clone.
FTRL

Examples

# Factorization Machines can fit XOR function!
x = rbind(
c(0, 0),
c(0, 1),
c(1, 0),
c(1, 1)
)
y = c(0, 1, 1, 0)

x = as(x, "RsparseMatrix")
fml = FactorizationMachine$new(learning_rate_w = 10, rank = 2, lambda_w = 0,
lambda_v = 0, family = 'binomial', intercept = TRUE)
res = fml$fit(x, y, n_iter = 100)
preds = fml$predict(x)
all(preds[1, 4] < 0.01)
all(preds[2, 3] > 0.99)

FTRL

Logistic regression model with FTRL proximal SGD solver.

Description

Creates 'Follow the Regularized Leader' model. Only logistic regression implemented at the moment.

Methods

Public methods:

• FTRL$new()
• FTRL$partial_fit()
• FTRL$fit()
• FTRL$predict()
• FTRL$coef()
• FTRL$clone()

Method new(): creates a model

Usage:
FTRL$new(
  learning_rate = 0.1,
  learning_rate_decay = 0.5,
  lambda = 0,
  l1_ratio = 1,
  dropout = 0,
  family = c("binomial")
)
Arguments:
learning_rate learning rate
learning_rate_decay learning rate which controls decay. Please refer to FTRL proximal paper for details. Usually convergence does not heavily depend on this parameter, so default value 0.5 is safe.
lambda regularization parameter
l1_ratio controls L1 vs L2 penalty mixing. 1 = Lasso regression, 0 = Ridge regression. Elastic net is in between
dropout dropout - percentage of random features to exclude from each sample. Acts as regularization.
family a description of the error distribution and link function to be used in the model. Only binomial (logistic regression) is implemented at the moment.

Method partial_fit(): fits model to the data
Usage:
FTRL$partial_fit(x, y, weights = rep(1, length(y)), ...)
Arguments:
x input sparse matrix. Native format is Matrix::RsparseMatrix. If x is in different format, model will try to convert it to RsparseMatrix with as(x, "RsparseMatrix"). Dimensions should be (n_samples, n_features)
y vector of targets
weights numeric vector of length 'n_samples'. Defines how to amplify SGD updates for each sample. May be useful for highly unbalanced problems.
... not used at the moment

Method fit(): shorthand for applying 'partial_fit' 'n_iter' times
Usage:
FTRL$fit(x, y, weights = rep(1, length(y)), n_iter = 1L, ...)
Arguments:
x input sparse matrix. Native format is Matrix::RsparseMatrix. If x is in different format, model will try to convert it to RsparseMatrix with as(x, "RsparseMatrix"). Dimensions should be (n_samples, n_features)
y vector of targets
weights numeric vector of length 'n_samples'. Defines how to amplify SGD updates for each sample. May be useful for highly unbalanced problems.
n_iter number of SGD epochs
... not used at the moment

Method predict(): makes predictions based on fitted model
Usage:
FTRL$predict(x, ...)
Arguments:
x input matrix
... not used at the moment
**Method** `coef()`: returns coefficients of the regression model

*Usage:*

```r
FTRL$coef()
```

**Method** `clone()`: The objects of this class are cloneable with this method.

*Usage:*

```r
FTRL$clone(deep = FALSE)
```

*Arguments:*

- `deep` Whether to make a deep clone.

**Examples**

```r
library(rsparse)
library(Matrix)
i = sample(1000, 1000 * 100, TRUE)
j = sample(1000, 1000 * 100, TRUE)
y = sample(c(0, 1), 1000, TRUE)
x = sample(c(-1, 1), 1000 * 100, TRUE)
odd = seq(1, 99, 2)
x[i %in% which(y == 1) & j %in% odd] = 1
m = sparseMatrix(i = i, j = j, x = x, dims = c(1000, 1000), giveCsparse = FALSE)
x = as(m, "RsparseMatrix")

ftrl = FTRL$new(learning_rate = 0.01, learning_rate_decay = 0.1, 
lambda = 10, l1_ratio = 1, dropout = 0)
ftrl$partial_fit(x, y)

w = ftrl$coef()
head(w)
sum(w != 0)
p = ftrl$predict(m)
```

---

**GloVe**

**Global Vectors**

**Description**

Creates Global Vectors matrix factorization model

**Public fields**

- `components` represents context embeddings
- `bias_i` bias term i as per paper
- `bias_j` bias term j as per paper
- `shuffle` logical = `FALSE` by default. Whether to perform shuffling before each SGD iteration. Generally shuffling is a good practice for SGD.
Methods

Public methods:

- GloVe$new()
- GloVe$fit_transform()
- GloVe$get_history()
- GloVe$clone()

Method new(): Creates GloVe model object

Usage:
GloVe$new(
  rank,
  x_max,
  learning_rate = 0.15,
  alpha = 0.75,
  lambda = 0,
  shuffle = FALSE,
  init = list(w_i = NULL, b_i = NULL, w_j = NULL, b_j = NULL)
)

Arguments:
rank desired dimension for the latent vectors
x_max integer maximum number of co-occurrences to use in the weighting function
learning_rate numeric learning rate for SGD. I do not recommend that you modify this parameter, since AdaGrad will quickly adjust it to optimal
alpha numeric = 0.75 the alpha in weighting function formula: \( f(x) = 1 \) if \( x > x_{max} \); else \( (x/x_{max})^alpha \)
lambda numeric = 0.0 regularization parameter
shuffle see shuffle field
init list(w_i = NULL, b_i = NULL, w_j = NULL, b_j = NULL) initialization for embeddings (w_i, w_j) and biases (b_i, b_j). w_i, w_j - numeric matrices, should have #rows = rank, #columns = expected number of rows (w_i) / columns(w_j) in the input matrix. b_i, b_j = numeric vectors, should have length of #expected number of rows(b_i) / columns(b_j) in input matrix

Method fit_transform(): fits model and returns embeddings

Usage:
GloVe$fit_transform(
  x,
  n_iter = 10L,
  convergence_tol = -1,
  n_threads = getOption("rsparse_omp_threads", 1L),
  ...
)

Arguments:
x An input term co-occurrence matrix. Preferably in dgTMatrix format
n_iter integer number of SGD iterations
convergence_tol numeric = -1 defines early stopping strategy. Stop fitting when one of two following conditions will be satisfied: (a) passed all iterations (b) cost_previous_iter / cost_current_iter -1 < convergence_tol.

n_threads number of threads to use
... not used at the moment

**Method** get_history(): returns value of the loss function for each epoch

*Usage:*
GloVe$get_history()

**Method** clone(): The objects of this class are cloneable with this method.

*Usage:*
GloVe$clone(deep = FALSE)

*Arguments:*
deep Whether to make a deep clone.

**References**


**Examples**

```r
data('movielens100k')
cost_occurrence = crossprod(movielens100k)
glove_model = GloVe$new(rank = 4, x_max = 10, learning_rate = .25)
embeddings = glove_model$fit_transform(cost_occurrence, n_iter = 2, n_threads = 1)
embeddings = embeddings + t(glove_model$components) # embeddings + context embeddings
identical(dim(embeddings), c(ncol(movielens100k), 10L))
```

---

**LinearFlow**

**Linear-Flow model for one-class collaborative filtering**

**Description**

Creates *Linear-Flow* model described in Practical Linear Models for Large-Scale One-Class Collaborative Filtering. The goal is to find item-item (or user-user) similarity matrix which is **low-rank and has small Frobenius norm**. Such double regularization allows to better control the generalization error of the model. Idea of the method is somewhat similar to **Sparse Linear Methods(SLIM)** but scales to large datasets much better.

**Super class**

`rsparse::MatrixFactorizationRecommender` -> LinearFlow

**Public fields**

v right singular vector of the user-item matrix. Size is n_items * rank. In the paper this matrix is called v
Methods

**Public methods:**

- `LinearFlow$new()`
- `LinearFlow$fit_transform()`
- `LinearFlow$transform()`
- `LinearFlow$cross_validate_lambda()`
- `LinearFlow$clone()`

**Method new():** creates Linear-FLOW model with rank latent factors.

*Usage:*

```r
LinearFlow$new(
  rank = 8L,
  lambda = 0,
  init = NULL,
  preprocess = identity,
  solve_right_singular_vectors = c("soft_impute", "svd")
)
```

*Arguments:*

- `rank` size of the latent dimension
- `lambda` regularization parameter
- `init` initialization of the orthogonal basis.
- `preprocess` identity() by default. User specified function which will be applied to user-item interaction matrix before running matrix factorization (also applied during inference time before making predictions). For example we may want to normalize each row of user-item matrix to have 1 norm. Or apply log1p() to discount large counts.
- `solve_right_singular_vectors` type of the solver for initialization of the orthogonal basis. Original paper uses SVD. See paper for details.

**Method fit_transform():** performs matrix factorization

*Usage:*

```r
LinearFlow$fit_transform(x, ...)
```

*Arguments:*

- `x` input matrix
- `...` not used at the moment

**Method transform():** calculates user embeddings for the new input

*Usage:*

```r
LinearFlow$transform(x, ...)
```

*Arguments:*

- `x` input matrix
- `...` not used at the moment

**Method cross_validate_lambda():** performs fast tuning of the parameter 'lambda' with warm re-starts
**Usage:**
LinearFlow$cross_validate_lambda(
  x,
  x_train,
  x_test,
  lambda = "auto@10",
  metric = "map@10",
  not_recommend = x_train,
  ...
)

**Arguments:**
x  input user-item interactions matrix. Model performs matrix factorization based only on this matrix
x_train  user-item interactions matrix. Model recommends items based on this matrix. Usually should be different from `x` to avoid overfitting
x_test  target user-item interactions. Model will evaluate predictions against this matrix, `x_test` should be treated as future interactions.
lambda  numeric vector - sequence of regularization parameters. Supports special value like `auto@10`. This will automatically fine a sequence of lambda of length 10. This is recommended way to check for `lambda`.
metric  a metric against which model will be evaluated for top-k recommendations. Currently only `map@k` and `ndcg@k` are supported (k can be any integer)
not_recommend  matrix same shape as `x_train`. Specifies which items to not recommend for each user.
...  not used at the moment

**Method** clone(): The objects of this class are cloneable with this method.

**Usage:**
LinearFlow$clone(deep = FALSE)

**Arguments:**
deep  Whether to make a deep clone.

**References**

**Examples**
data("movielens100k")
train = movielens100k[1:900, ]
cv = movielens100k[901:nrow(movielens100k), ]
model = LinearFlow$new(
  rank = 10, lambda = 0,
  solve_right_singular_vectors = "svd"
)
user_emb = model$fit_transform(train)
preds = model$predict(cv, k = 10)
Multithreaded Sparse-Dense Matrix Multiplication

Description

Multithreaded %*%, crossprod, tcrossprod for sparse-dense matrix multiplication

Usage

```r
## S4 method for signature 'dgRMatrix, matrix'
x %*% y
## S4 method for signature 'dgRMatrix, float32'
x %*% y
## S4 method for signature 'float32, dgRMatrix'
x %*% y
## S4 method for signature 'dgRMatrix, matrix'
tcrossprod(x, y)
## S4 method for signature 'dgRMatrix, float32'
tcrossprod(x, y)
## S4 method for signature 'matrix, dgCMatrix'
x %*% y
## S4 method for signature 'float32, dgCMatrix'
x %*% y
## S4 method for signature 'dgCMatrix, float32'
x %*% y
## S4 method for signature 'matrix, dgCMatrix'
tcrossprod(x, y)
## S4 method for signature 'float32, dgCMatrix'
tcrossprod(x, y)
```

Arguments

- `x, y` dense matrix and sparse Matrix::RsparseMatrix/Matrix::CsparseMatrix matrices.
Details
Accelerates sparse-dense matrix multiplications using openmp. Applicable to the following pairs: (dgRMatrix, matrix), (matrix, dgRMatrix), (dgCMatrix, matrix), (matrix, dgCMatrix) combinations

Value
A dense matrix

Examples
```r
library(Matrix)
data("movielens100k")
k = 10
nc = ncol(movielens100k)
nr = nrow(movielens100k)
x_nc = matrix(rep(1:k, nc), nrow = nc)
x_nr = t(matrix(rep(1:k, nr), nrow = nr))
csc = movielens100k
csr = as(movielens100k, "RsparseMatrix")
dense = as.matrix(movielens100k)
identical(csr %*% x_nc, dense %*% x_nc)
identical(x_nr %*% csc, x_nr %*% dense)
```

metrics Ranking Metrics for Top-K Items

Description
ap_k calculates Average Precision at K (ap@k). Please refer to Information retrieval wikipedia article
ndcg_k() calculates Normalized Discounted Cumulative Gain at K (ndcg@k). Please refer to Discounted cumulative gain

Usage
```r
ap_k(predictions, actual, ...)

ndcg_k(predictions, actual, ...)
```

Arguments
```
predictions  matrix of predictions. Predictions can be defined 2 ways:
1. predictions = integer matrix with item indices (correspond to column numbers in actual)
2. predictions = character matrix with item identifiers (characters which correspond to colnames(actual)) which has attribute "indices" (integer matrix with item indices which correspond to column numbers in actual).
```
actual sparse Matrix of relevant items. Each non-zero entry considered as relevant item. Value of the each non-zero entry considered as relevance for calculation of ndcg@k. It should inherit from Matrix::sparseMatrix. Internally Matrix::RsparseMatrix is used.

... other arguments (not used at the moment)

Examples

```r
predictions = matrix(
  c(5L, 7L, 9L, 2L),
  nrow = 1
)
actual = matrix(
  c(0, 0, 0, 0, 1, 0, 1, 0, 1, 0),
  nrow = 1
)
actual = as(actual, "RsparseMatrix")
identical(rsparse::ap_k(predictions, actual), 1)
```

---

**movielens100k**  
**MovieLens 100K Dataset**

**Description**

This data set consists of:

1. 100,000 ratings (1-5) from 943 users on 1682 movies.
2. Each user has rated at least 20 movies.

MovieLens data sets were collected by the GroupLens Research Project at the University of Minnesota.

**Usage**

```r
data("movielens100k")
```

**Format**

A sparse column-compressed matrix (Matrix::dgCMatrix) with 943 rows and 1682 columns.

1. rows are users
2. columns are movies
3. values are ratings

**Source**

[https://en.wikipedia.org/wiki/MovieLens#Datasets](https://en.wikipedia.org/wiki/MovieLens#Datasets)
PureSVD

Description

Creates PureSVD recommender model. Solver is based on Soft-SVD which is very similar to truncated SVD but optionally adds regularization based on nuclear norm.

Super class

rsparse::MatrixFactorizationRecommender -> PureSVD

Methods

Public methods:

• PureSVD$new()
• PureSVD$fit_transform()
• PureSVD$transform()
• PureSVD$clone()

Method new(): create PureSVD model

Usage:

PureSVD$new(
  rank = 10L,
  lambda = 0,
  init = NULL,
  preprocess = identity,
  method = c("svd", "impute"),
  ...
)

Arguments:

rank  size of the latent dimension
lambda  regularization parameter
init  initialization of item embeddings
preprocess  identity() by default. User specified function which will be applied to user-item interaction matrix before running matrix factorization (also applied during inference time before making predictions). For example we may want to normalize each row of user-item matrix to have 1 norm. Or apply log1p() to discount large counts.
method  type of the solver for initialization of the orthogonal basis. Original paper uses SVD. See paper for details.
...  not used at the moment

Method fit_transform(): performs matrix factorization

Usage:
PureSVD$fit_transform(x, n_iter = 100L, convergence_tol = 0.001, ...)

**Arguments:**
- **x** input sparse user-item matrix (of class dgCMatrix)
- **n_iter** maximum number of iterations
- **convergence_tol** numeric = -Inf defines early stopping strategy. Stops fitting when one of two following conditions will be satisfied: (a) passed all iterations (b) relative change of Frobenious norm of the two consequent solution is less then provided convergence_tol.

... not used at the moment

**Method** `transform()`: calculates user embeddings for the new input

**Usage:**
PureSVD$transform(x, ...)

**Arguments:**
- **x** input matrix

... not used at the moment

**Method** `clone()`: The objects of this class are cloneable with this method.

**Usage:**
PureSVD$clone(deep = FALSE)

**Arguments:**
- **deep** Whether to make a deep clone.

**Examples**

```r
data('movielens100k')
i_train = sample(nrow(movielens100k), 900)
i_test = setdiff(seq_len(nrow(movielens100k)), i_train)
train = movielens100k[i_train, ]
test = movielens100k[i_test, ]
rank = 32
lambda = 0
model = PureSVD$new(rank = rank, lambda = lambda)
user_emb = model$fit_transform(sign(test), n_iter = 100, convergence_tol = 0.00001)
item_emb = model$components
preds = model$predict(sign(test), k = 1500, not_recommend = NULL)
mean(ap_k(preds, actual = test))
```

**ScaleNormalize**

Re-scales input matrix proportinally to item popularity

**Description**

scales input user-item interaction matrix as per eq (16) from the paper. Usage of such rescaled matrix with [PureSVD] model will be equal to running PureSVD on the scaled cosine-based inter-item similarity matrix.
Public fields

- `norm` which norm model should make equal to one
- `scale` how to rescale norm vector

Methods

Public methods:

- `ScaleNormalize$new()`
- `ScaleNormalize$fit()`
- `ScaleNormalize$transform()`
- `ScaleNormalize$fit_transform()`
- `ScaleNormalize$clone()`

Method `new()`: creates model

Usage:

```
ScaleNormalize$new(scale = 0.5, norm = 2, target = c("rows", "columns"))
```

Arguments:

- `scale` numeric, how to rescale norm vector
- `norm` numeric, which norm model should make equal to one
- `target` character, defines whether rows or columns should be rescaled

Method `fit()`: fits the modes

Usage:

```
ScaleNormalize$fit(x)
```

Arguments:

- `x` input sparse matrix

Method `transform()`: transforms new matrix

Usage:

```
ScaleNormalize$transform(x)
```

Arguments:

- `x` input sparse matrix

Method `fit_transform()`: fits the model and transforms input

Usage:

```
ScaleNormalize$fit_transform(x)
```

Arguments:

- `x` input sparse matrix

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
ScaleNormalize$clone(deep = FALSE)
```

Arguments:

- `deep` Whether to make a deep clone.
References

See EigenRec: Generalizing PureSVD for Effective and Efficient Top-N Recommendations for details.

---

slice

**CSR Matrices Slicing**

**Description**

natively slice CSR matrices without converting them to triplet/CSC

**Usage**

```r
## S4 method for signature 'RsparseMatrix,index,index,logical'
x[i, j, drop = TRUE]
```

```r
## S4 method for signature 'RsparseMatrix,missing,index,logical'
x[i, j, drop = TRUE]
```

```r
## S4 method for signature 'RsparseMatrix,index,missing,logical'
x[i, j, drop = TRUE]
```

```r
## S4 method for signature 'RsparseMatrix,missing,missing,logical'
x[i, j, drop = TRUE]
```

**Arguments**

- `x`: input RsparseMatrix
- `i`: row indices to subset
- `j`: column indices to subset
- `drop`: whether to simplify 1d matrix to a vector

**Value**

A RsparseMatrix

**Examples**

```r
library(Matrix)
library(rsparse)
# dgCMatrix - CSC
m = rsparsematrix(20, 20, 0.1)
# make CSR
m = as(m, "RsparseMatrix")
inherits(m[1:2, ], "RsparseMatrix")
inherits(m[1:2, 3:4], "RsparseMatrix")
```
soft_impute

**SoftImpute/SoftSVD matrix factorization**

**Description**


**Usage**

```r
soft_impute(
  x,
  rank = 10L,
  lambda = 0,
  n_iter = 100L,
  convergence_tol = 0.001,
  init = NULL,
  final_svd = TRUE
)

soft_svd(
  x,
  rank = 10L,
  lambda = 0,
  n_iter = 100L,
  convergence_tol = 0.001,
  init = NULL,
  final_svd = TRUE
)
```

**Arguments**

- `x`: sparse matrix. Both CSR `dgRMatrix` and CSC `dgCMatrix` are supported. CSR matrix is preferred because in this case the algorithm will benefit from multithreaded CSR * dense matrix products (if OpenMP is supported on your platform). On many-cores machines this reduces fitting time significantly.
- `rank`: maximum rank of the low-rank solution.
- `lambda`: regularization parameter for the nuclear norm
- `n_iter`: maximum number of iterations of the algorithms
- `convergence_tol`: convergence tolerance. Internally functions keep track of the relative change of the Frobenious norm of the two consequent iterations. If the change is less than `convergence_tol` then the process is considered as converged and function returns result.
init  svd-like object with u, v, d components to initialize algorithm. Algorithm benefit from warm starts. init could be rank up rank of the maximum allowed rank. If init has rank less than max rank it will be padded automatically.

final_svd  logical whether need to make final preprocessing with SVD. This is not necessary but cleans up rank nicely - highly recommended to leave it TRUE.

Value

svd-like object - list(u, v, d). u, v, d components represent left, right singular vectors and singular values.

Examples

```r
set.seed(42)
data('movielens100k')
k = 10
seq_k = seq_len(k)
m = movielens100k[1:100, 1:200]
svd_ground_true = svd(m)
svd_soft_svd = soft_svd(m, rank = k, n_iter = 100, convergence_tol = 1e-6)
m_restored_svd = svd_ground_true$u[, seq_k] %*% diag(x = svd_ground_true$d[seq_k]) %*% t(svd_ground_true$v[, seq_k])
m_restored_soft_svd = svd_soft_svd$u %*% diag(x = svd_soft_svd$d) %*% t(svd_soft_svd$v)
all.equal(m_restored_svd, m_restored_soft_svd, tolerance = 1e-1)
```

Description

Creates matrix factorization model which could be solved with Alternating Least Squares (Weighted ALS for implicit feedback). For implicit feedback see "Collaborative Filtering for Implicit Feedback Datasets" (Hu, Koren, Volinsky). For explicit feedback model is classic model for rating matrix decomposition with MSE error (without biases at the moment). These two algorithms are proven to work well in recommender systems.

Super class

rsparse::MatrixFactorizationRecommender -> WRMF

Methods

Public methods:

- WRMF$new()
- WRMF$fit_transform()
• `WRMF$transform()`
• `WRMF$clone()`

**Method** `new()`: creates WRMF model

**Usage**:

```r
WRMF$new(
    rank = 10L,
    lambda = 0,
    init = NULL,
    preprocess = identity,
    feedback = c("implicit", "explicit"),
    non_negative = FALSE,
    solver = c("conjugate_gradient", "cholesky"),
    cg_steps = 3L,
    precision = c("double", "float"),
    ...
)
```

**Arguments**:

- `rank` size of the latent dimension
- `lambda` regularization parameter
- `init` initialization of item embeddings
- `preprocess` identity() by default. User specified function which will be applied to user-item interaction matrix before running matrix factorization (also applied during inference time before making predictions). For example we may want to normalize each row of user-item matrix to have 1 norm. Or apply `log1p()` to discount large counts. This corresponds to the "confidence" function from "Collaborative Filtering for Implicit Feedback Datasets" paper.
- `feedback` character - feedback type - one of `c("implicit","explicit")`
- `non_negative` logical, whether to perform non-negative factorization
- `solver` character - solver for "implicit feedback" problem. One of `c("conjugate_gradient","cholesky")`. Usually approximate "conjugate_gradient" is significantly faster and solution is on par with "cholesky"
- `cg_steps` integer > 0 - max number of internal steps in conjugate gradient (if "conjugate_gradient" solver used). 3L by default. Controls precision of linear equation solution at the each ALS step. Usually no need to tune this parameter
- `precision` one of `c("double","float")`. Should embedding matrices be numeric or float (from float package). The latter is usually 2x faster and consumes less RAM. BUT float matrices are not "base" objects. Use carefully.
- `...` not used at the moment

**Method** `fit_transform()`: fits the model

**Usage**:

```r
WRMF$fit_transform(x, n_iter = 10L, convergence_tol = 0.005, ...)
```

**Arguments**:

- `x` input matrix (preferably matrix in CSC format - 'CsparseMatrix')
n_iter  max number of ALS iterations
convergence_tol convergence tolerance checked between iterations
... not used at the moment

**Method** `transform()`: create user embeddings for new input

*Usage:*

```r
WRMF$transform(x, ...)
```

*Arguments:*

- `x` user-item interaction matrix
- ... not used at the moment

**Method** `clone()`: The objects of this class are cloneable with this method.

*Usage:*

```r
WRMF$clone(deep = FALSE)
```

*Arguments:*

- `deep` Whether to make a deep clone.

**References**

- [https://jessesw.com/Rec-System/](https://jessesw.com/Rec-System/)

**Examples**

```r
data('movielens100k')
train = movielens100k[1:900, ]
CV = movielens100k[901:nrow(movielens100k), ]
model = WRMF$new(rank = 5, lambda = 0, feedback = 'implicit')
user_emb = model$fit_transform(train, n_iter = 5, convergence_tol = -1)
item_emb = model$components
preds = model$predict(CV, k = 10, not_recommend = CV)
```
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