Package ‘rsparse’

October 14, 2022

Type Package
Title Statistical Learning on Sparse Matrices
Version 0.5.1
Maintainer Dmitriy Selivanov <ds@rexy.ai>
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:

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.

License GPL (>= 2)
Encoding UTF-8
LazyData true
ByteCompile true
detect_number_omp_threads

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

Usage

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:

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 interactions
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 intercept 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.

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

---

**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:**

```r
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:*
FTRL$coef()

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

*Usage:*
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
x = sparseMatrix(i = i, j = j, x = x, dims = c(1000, 1000), repr="R")

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(x)
```

---

### 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 \( x > x_{\text{max}} \); \( \frac{x}{x_{\text{max}}}^{\alpha} \) else
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.
LinearFlow

Usage:
GloVe$clone(deep = FALSE)

Arguments:
deep Whether to make a deep clone.

References
http://nlp.stanford.edu/projects/glove/

Examples

data('movielens100k')
co_occurence = crossprod(movielens100k)
glove_model = GloVe$new(rank = 4, x_max = 10, learning_rate = .25)
embeddings = glove_model$fit_transform(co_occurence, n_iter = 2, n_threads = 1)
embeddings = embeddings + t(glove_model$components) # embeddings + context embedings
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 LinearFlow model with rank latent factors.

Usage:
```
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:
```
LinearFlow$fit_transform(x, ...)
```

Arguments:
- **x**: input matrix
- **...**: not used at the moment

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

Usage:
```
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:
dee  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)

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

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 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

predictions = matrix(
c(5L, 7L, 9L, 2L),
nrow = 1
)
actual = matrix(
c(0, 0, 0, 1, 0, 1, 0, 1, 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

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)

---

**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:*

```r
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

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 proportionally 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:*

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

*Arguments:*

- `x` input sparse matrix

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

*Usage:*

```r
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.

---

**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
)
```

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

x \text{ sparse matrix. Both CSR \texttt{dgRMatrix} and CSC \texttt{dgCMatrix} are supported. CSR matrix is preffered because in this case 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.}

\text{rank} \text{ maximum rank of the low-rank solution.}

\text{lambda} \text{ regularization parameter for the nuclear norm}

\text{n_iter} \text{ maximum number of iterations of the algorithms}

\text{convergence_tol} \text{ convergence tolerance. Internally functions keeps 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.}

\text{init} \text{ svd like object with } u, v, d \text{ 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.}

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

Value

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

Examples

\text{set.seed(42)}
\text{data('movielens100k')}
\text{k = 10}
\text{seq_k = seq_len(k)}
\text{m = movielens100k[1:100, 1:200]}
\text{svd\_ground\_true = svd(m)}
\text{svd\_soft\_svd = soft\_svd(m, rank = k, n\_iter = 100, convergence\_tol = 1e-6)}
\text{m\_restored\_svd = svd\_ground\_true\$u[, seq_k] %*% diag(x = svd\_ground\_true\$d[seq_k]) %*% t(svd\_ground\_true\$v[, seq_k])}
\text{m\_restored\_soft\_svd = svd\_soft\_svd\$u %*% diag(x = svd\_soft\_svd\$d) %*% t(svd\_soft\_svd\$v)}
\text{all.equal(m\_restored\_svd, m\_restored\_soft\_svd, tolerance = 1e-1)
Description

Creates a matrix factorization model which is solved through Alternating Least Squares (Weighted ALS for implicit feedback). For implicit feedback see “Collaborative Filtering for Implicit Feedback Datasets” (Hu, Koren, Volinsky). For explicit feedback it corresponds to the classic model for rating matrix decomposition with MSE error. 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:

WRMF$new(
  rank = 10L,
  lambda = 0,
  dynamic_lambda = TRUE,
  init = NULL,
  preprocess = identity,
  feedback = c("implicit", "explicit"),
  solver = c("conjugate_gradient", "cholesky", "nnls"),
  with_user_item_bias = FALSE,
  with_global_bias = FALSE,
  cg_steps = 3L,
  precision = c("double", "float"),
  ...
)

Arguments:

rank  size of the latent dimension
lambda  regularization parameter
dynamic_lambda  whether ‘lambda’ is to be scaled according to the number
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. Note that it will not automatically add +1 to the weights of the positive entries.

feedback character - feedback type - one of c("implicit", "explicit")
solver character - solver name. One of c("conjugate_gradient", "cholesky", "nnls"). Usually approximate "conjugate_gradient" is significantly faster and solution is on par with "cholesky". "nnls" performs non-negative matrix factorization (NNMF) - restricts user and item embeddings to be non-negative.

with_user_item_bias bool controls if model should calculate user and item biases. At the moment only implemented for "explicit" feedback.

with_global_bias bool controls if model should calculate global biases (mean). At the moment only implemented for "explicit" feedback.

cg_steps integer > 0 - max number of internal steps in conjugate gradient (if "conjugate_gradient" solver used). cg_steps = 3 by default. Controls precision of linear equation solution at 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$fit_transform(x,  
    n_iter = 10L,  
    convergence_tol = ifelse(private$feedback == "implicit", 0.005, 0.001),  
    ...  
)
```

*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 (preferably as 'dgRMatrix')  
... not used at the moment

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

WRMF$clone(deep = FALSE)

Arguments:

depth Whether to make a deep clone.

References

- 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)
```
Index

* datasets
  movielens100k, 12
ap_k(metrics), 11
detect_number_omp_threads, 2
FactorizationMachine, 3
FTRL, 5
GloVe, 7
LinearFlow, 9
metrics, 11
movielens100k, 12
ndcg_k(metrics), 11
PureSVD, 13
rsparse::MatrixFactorizationRecommender,
  9, 13, 18
ScaleNormalize, 15
soft_impute, 16
soft_svd(soft_impute), 16
svd, 17
WRMF, 18