Package ‘rrecsys’

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**Type** Package

**Title** Environment for Evaluating Recommender Systems

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**URL** https://rrecsys.inf.unibz.it/

**BugReports** https://github.com/ludovikcoba/rrecsys/issues

**Description** Processes standard recommendation datasets (e.g., a user-item rating matrix) as input and generates rating predictions and lists of recommended items. Standard algorithm implementations which are included in this package are the following: Global/Item/User-Average baselines, Weighted Slope One, Item-Based KNN, User-Based KNN, FunkSVD, BPR and weighted ALS. They can be assessed according to the standard offline evaluation methodology (Shani, et al. (2011) <doi:10.1007/978-0-387-85820-3_8>) for recommender systems using measures such as MAE, RMSE, Precision, Recall, F1, AUC, NDCG, RankScore and coverage measures. The package (Coba, et al. (2017) <doi: 10.1007/978-3-319-60042-0_36>) is intended for rapid prototyping of recommendation algorithms and education purposes.

**Imports** methods, Rcpp

**Depends** R (>= 3.1.2), registry, MASS, stats, knitr, ggplot2

**License** GPL-3

**VignetteBuilder** knitr

**Encoding** UTF-8

**Repository** CRAN

**LinkingTo** Rcpp

**NeedsCompilation** yes

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Baseline algorithms exploiting global/item and user averages.

Container for the model learned using any average(global, user or item) based model.

**Slots**

- **alg:** The algorithm denominator, of class "character".
- **data:** the dataset used for training the model, class "matrix".
- **average:** average calculated either globally, on user or item, class "matrix".
Methods

show signature(object = "algAverageClass")

See Also

rrecsys.

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**BPRclass**

*Bayesian Personalized Ranking based model.*

**Description**

Container for the model learned using any Bayesian Personalized Ranking based model.

**Slots**

- **alg**: The algorithm denominator, of class "character".
- **data**: the dataset used for training the model, class "matrix".
- **factors**: user(U) and items(V) factors, class "list".
- **parameters**: the parameters(such as number of factors k, learning rate \( \lambda \), user regularization term \( \text{regU} \), positive rated item regularization term \( \text{regI} \), negative rated item regularization term \( \text{regJ} \) and the Boolean \( \text{updateJ} \) to decide whatever negative updates are required) used in the model, class "list".

**Methods**

show signature(object = "BPRclass")

See Also

rrecsys.

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**dataChart**

*Visualization of data characteristics.*

**Description**

This method visualizes data characteristics on a two dimensional graph, where "x" axes shows either items ordered by descending popularity, or users based on the number of ratings they have submitted. Moreover the "y" axes shows the number of ratings.

**Usage**

dataChart(data, x = "items", y = "num_of_ratings")
Arguments

data  the dataset, class "_ds".

x  class "character", is the variable that will be shown on the "x" axis. Possible values are: "items", "users".

y  class "character", is the variable that will be shown on the "y" axis. Possible values are: "num_of_ratings", "%_of_ratings".

Value

Plot results.

See Also

See Also as _ds-class.

Examples

data(mlLatest100k)
da <- defineData(mlLatest100k)
dataChart(a, x = "items", y = "num_of_ratings")

 dataSet-class  Dataset class.

Description

Container for a dense dataset that distinguishes between binary and non-binary feedback datasets. Extends _ds.

Slots

data: the dataset, class "matrix".

binary: class "logical", determines if the item dataset contains binary (i.e. 1/0) or non-binary ratings.

minimum: class "numeric", defines the minimal value present in the dataset.

maximum: class "numeric", defines the maximal value present in the dataset.

intScale: object of class "logical", if TRUE the range of ratings in the dataset contains as well half star values.
**defineData**

*Define dataset.*

**Methods**

- `nrow` signature(object = "dataSet"): number of rows of the dataset.
- `ncol` signature(object = "dataSet"): number of columns of the dataset.
- `dim` signature(object = "dataSet"): returns the dimensions of the dataset.
- `rowRatings` signature(object = "dataSet"): returns the number of ratings on each row.
- `colRatings` signature(object = "dataSet"): returns the number of ratings on each column.
- `numRatings` signature(object = "dataSet"): returns the total number of ratings.
- `[` signature(x = "dataSet", i = "ANY", j = "ANY", drop = "ANY"): returns a subset of the dataset.
- `coerce` signature(from = "dataSet", to = "matrix")
- `rowAverages` signature(object = "dataSet"): returns the average rating on each row.
- `colAverages` signature(object = "dataSet"): returns the average rating on each column.

**Examples**

```r
x <- matrix(sample(c(0:5), size = 100, replace = TRUE,
                   prob = c(.6,.08,.08,.08,.08,.08)), nrow = 20, byrow = TRUE)

x <- defineData(x)

colRatings(x)
rowRatings(x)
numRatings(x)
sparsity(x)

a <- x[1:10,2:3]
```

**Description**

Defines your dataset, if either it is implicit or explicit.

**Arguments**

- `data` the dataset, class "matrix".
- `sparseMatrix` class "logical". If FALSE implies that the input is a dense two dimensional matrix. If TRUE implies that the input is arranged as coordinate list where entries are stored as list of (row, column, value) tuples.
binary class "logical", defines if the item dataset consists of binary (i.e. NA/1) or non-binary ratings. Default value FALSE.

minimum class "numeric", defines the minimal value present in the dataset. Default value 0.5.

maximum class "numeric", defines the maximal value present in the dataset. Default value 5.

intScale object of class "logical", if TRUE the range of ratings in the dataset contains as well half star values. Default value FALSE.

positiveThreshold class "numeric", in case binary is TRUE, positiveThreshold defines the threshold value for binarizing the dataset (i.e. any rating value >= positiveThreshold will be transformed to 1 and all other values to NA(corresponding to a not rated item). Default value 0.5.

Value

Returns an object of class "dataSet".

See Also

See Also as dataSet-class.

Examples

data(mlLatest100k)

a <- defineData(mlLatest100k)

b <- defineData(mlLatest100k,binary = TRUE ,positiveThreshold = 3)

data(mlLatest100k)
**evalModel**

Creating the evaluation model.

**Arguments**

res | evaluation results, class "evalRecResults".
--- | ---
x | class "character", is the variable that will be shown on the "x" axis. Possible values are: "items", "users".
y | class "character", is the variable that will be shown on the "y" axis. Possible values are: "num_of_ratings", "% of ratings".
x_label | class "character", the label to be printed on the "x" axes.
y_label | class "character", the label to be printed on the "y" axes.
y_lim | class "numeric", scale of the "y" axes.

**Value**

Plot results.

**See Also**

See Also as **evalRecResults-class**.

**Description**

Creates the dataset split for evaluation where ratings of each user are uniformly distributed over k random folds. The function returns the list of items that are assigned to each fold, such that algorithms can be compared on the same train/test splits.

**Usage**

evalModel(data, folds)

**Arguments**

data | dataset, of class _ds.
--- | ---
folds | The number of folds to use in the k-fold cross validation, of class numeric, default value set to 5.

**Value**

An object of class **evalModel-class**.

**See Also**

evalModel-class, evalRec, _ds.
**Examples**

```r
x <- matrix(sample(c(0:5), size = 200, replace = TRUE, prob = c(0.08, 0.08, 0.08, 0.08)), nrow = 20, byrow = TRUE)

d <- defineData(x)

my_2_folds <- evalModel(d, 2)  # output class evalModel.

my_2_folds
# 2-fold cross validation model on the dataset with 20 users and 10 items.

my_2_folds$data  # the dataset.
my_2_folds$folds  # the number of folds in the model.
my_2_folds$fold_indices  # the index of each item in the fold.
```

---

**evalModel-class**

*Evaluation model.*

**Description**

Class that contains the data and a distribution of the uniform distribution of ratings onto k-folds.

**Details**

The `fold_indices` list contains the indexes to access the dataset on one dimension. A matrix can be addressed as a one dimensional array, considered as an extension of each column after another. E.g: in a matrix `M` with 10 rows and 20 columns, `M[10] == M[10, 1]; M[12] == M[2,2].`

**Slots**

- `data`: the dataset, class "matrix".
- `folds`: number of k-folds, class "numeric".
- `fold_indices`: a list with k slots, each slot represents a fold and contains the index of items assigned to that fold, class "list".
- `fold_indices_x_user`: a list that specifies specifically for each user the distribution of the items in the folds, class "list".

**Methods**

- `show` signature(object = "evalModel")
**Description**

Evaluates the prediction task of an algorithm with a given configuration and based on the given evaluation model. RMSE and MAE are both calculated individually for each user and then averaged over all users (in this case they will be referred as RMSE and MAE) as well as determined as the average error over all predictions (in this case they are named globalRMSE and globalMAE).

**Usage**

```r
evalPred(model, ...)  
## S4 method for signature 'evalModel'
 evalPred(model, alg, ...)  
```

**Arguments**

- `model`: Object of type `evalModel`. See `evalModel-class`.  
- `alg`: The algorithm to be used in the evaluation. Of type character.  
- `...`: other attributes specific to the algorithm to be deployed. Refer to `rrecsys`.  

**Value**

Returns a data frame with the `rmse`, `mae`, `globalrmse` and `globalmae` for each of the k-folds defined in the evaluation model and an average over all folds.

**References**


**See Also**

`evalModel-class`, `rrecsys`.

**Examples**

```r
x <- matrix(sample(c(0:5), size = 200, replace = TRUE,  
prob = c(.6,.8,.8,.8,.8,.8)), nrow = 20, byrow = TRUE)

e <- defineData(x)

e <- evalModel(x, 2)

SVDEvaluation <- evalPred(e, "FunkSVD", k = 4)

SVDEvaluation
```
IBEvaluation <- evalPred(e, "IBKNN", simFunct = "cos", neigh = 5, coRatedThreshold = 2)

IBEvaluation

evalRec  Evaluates the requested recommendation algorithm.

Description
Evaluates the recommendation task of an algorithm with a given configuration and based on the given evaluation model.

Arguments
- **model**: Object of type `evalModel`. See `evalModel-class`.
- **alg**: The algorithm to be used in the evaluation. Of class `character`.
- **topN**: Object of class `numeric`, specifying the number of items to be recommended per user.
- **topNGen**: Object of class `character`, specifying the function used to produce the recommendations. Values: "hpr" and "mf" (currently available only for IB and UB methods).
- **positiveThreshold**: Object of class `numeric`, indicating the threshold of the ratings to be considered a good. This attribute is not used when evaluating implicit feedback.
- **alpha**: Object of class `numeric`, is the half-life parameter for the rankscore metric.
- **...**: other attributes specific to the algorithm to be deployed. Refer to `rrecsys`.

Value
Returns an object of class `evalRecResults` with the precision, recall, F1, nDCG, RankScore, true positives(TP), false positives(FP), true negatives(TN), false negatives(FN) for each of the k-folds defined in the evaluation model and the overall average.

References

See Also
`evalModel-class`, `rrecsys`, `evalRecResults-class`. 
evalRecResults

Examples

x <- matrix(sample(c(0:5), size = 200, replace = TRUE, prob = c(.6,.8,.8,.8,.8,.8)), nrow = 20, byrow = TRUE)

x <- defineData(x)

e <- evalModel(x, 2)

SVDEvaluation <- evalRec(e, "FunkSVD", positiveThreshold = 4, k = 4)

SVDEvaluation

evalRecResults  Evaluation results.

Description

Defines a structure for the results obtained by evaluating an algorithm.

Slots

data: class "_ds", the dataset.
alg: class "character", the name of the used algorithm.
topN: class "numeric", the number N of Top-N items recommended to each user.
topNGen: class "character", the name of the recommendation algorithm.
predicate: class "numeric", indicating the threshold of the ratings to be considered a good. This attribute is not used when evaluating implicit feedback.
alpha: class numeric, is the half-life parameter for the rankscore metric.
parameters: class "list", parameters used in the configuration of the algorithm.
TP: class "numeric", True Positives count on each fold.
FP: class "numeric", False Positives count on each fold.
TN: class "numeric", True Negatives count on each fold.
FN: class "numeric", False Negatives count on each fold.
precision: class "numeric", precision measured on each fold.
recall: class "numeric", recall measured on each fold.
F1: class "numeric", F1 measured on each fold.
nDCG: class "numeric", nDCG measured on each fold.
rankscore: class "numeric", rankscore measured on each fold.
item_coverage: class "numeric", item coverage.
user_coverage: class "numeric", user coverage.
ex.time: class "numeric", the execution time.
TP_count: class "numeric", True positives count on each item.
rec_counts: class "numeric", counts how many times an item was recommended.
rec_popularity: class "numeric", popularity of recommendations.

Methods

show signature(object = "evalRecResults")
results signature(object = "evalRecResults", metrics = "character"): returns a subset of the results based on the required metric.

eval_nDCG

Normalized Discounted Cumulative Gain

Description

Metric for information retrieval where positions are discounted logarithmically.

Usage

eval_nDCG(recommendedIDX, testSetIDX)

Arguments

recommendedIDX indices of the recommended items. Object of class numeric.
testSetIDX indices of the items in the test set. Object of class numeric

Details

nDCG is computed as the ratio between Discounted Cumulative Gain(DCG) and idealized Discounted Cumulative Gain(IDCG):

\[ DGC_{pos} = rel_1 + \sum_{i=2}^{pos} \frac{rel_i}{\log_2 i} \]

\[ IDGC_{pos} = rel_1 + \sum_{i=2}^{\vert h \vert - 1} \frac{rel_i}{\log_2 i} \]

\[ nDCG_{pos} = \frac{DCG}{IDCG} \]

References

Asela Gunawardana, Guy Shani, Evaluating Recommender Systems.
getAUC

Returns the Area under the ROC curve.

Description

Computes the Area Under the ROC curve for a recommendation task of an algorithm with its given configuration and based on the given evaluation model.

Usage

getauc(model, ...)  
## S4 method for signature 'evalModel'
  getauc(model, alg, ... )

Arguments

- model: Object of type evalModel. See evalModel-class.
- alg: The algorithm to be used in the evaluation. Of class character.
- ...: other attributes specific to the algorithm to be deployed. Refer to rrecsys.

Value

Returns a data frame with the AUC for each of the k-folds defined in the evaluation model and the overall average.

References


See Also
evalModel-class, rrecsys.

Examples

```r
  x <- matrix(sample(c(NA, 1:5), size = 200, replace = TRUE,  
                 prob = c(0.6, 0.8, 0.8, 0.8, 0.8)), nrow = 20, byrow = TRUE)
  x <- defineData(x)
  e <- evalModel(x, 5)
  auc <- getAUC(e, "FunkSVD", k = 4)
  auc
```
### histogram

*Ratings histogram.*

#### Description

Histogram of the ratings grouped by value.

#### Usage

```r
histogram(data, title = "", x = "Rating values", y = "# of ratings")
```

#### Arguments

- **data**: class "_ds", the dataset.
- **title**: class "character", eventual caption of for the chart.
- **x**: class "character", label for the x-axis.
- **y**: class "character", label for the y-axis.

### IBclass

*Item based model.*

#### Description

Container for the model learned using any k-nearest neighbor item-based collaborative filtering algorithm.

#### Slots

- **alg**: The algorithm denominator, of class "character".
- **data**: the dataset used for training the model, class "matrix".
- **sim**: The item - item similarity matrix, class "matrix".
- **sim_index_kNN**: The index of the k nearest neighbors for each item, class "matrix".
- **parameters**: the parameters used in the model, class "list".

#### Methods

- **show** signature(object = "IBclass")

#### See Also

`rrecsys`.
**Movielens 100K Dataset**

**Description**

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

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.

The data was collected through the MovieLens web site (movielens.umn.edu) during the seven-month period from September 19th, 1997 through April 22nd, 1998. This data has been cleaned up - users who had less than 20 ratings or did not have complete demographic information were removed from this data set. Detailed descriptions of the data file can be found at the end of this file.

**Source**

http://grouplens.org/datasets/movielens/100k/

---

**Movielens Latest**

**Description**

This dataset (ml-latest-small) is a 5-star rating dataset from [MovieLens](http://movielens.org), a movie recommendation service of the GroupLens research group at the University of Minnesota. It contains 100234 ratings across 8927 movies. The data was created by 718 users between March 26, 1996 and August 05, 2015. This dataset was generated on August 06, 2015. Users were selected at random for inclusion. All selected users had rated at least 20 movies. The data is edited and structured as a matrix and distributed as such. Below the usage license of this redistributed data is cited below.

**Usage**

data("mlLatest100k")

**Format**

The format is: num [1:718, 1:8915] 5 3 0 0 4 4 0 3 0 0 ... - attr(*, "dimnames")=List of 2 ..$ : chr [1:718] "1" "2" "3" "4" ... ..$ : chr [1:8915] "Toy Story (1995)" "Jumanji (1995)" "GoldenEye (1995)" "Twelve Monkeys (a.k.a. 12 Monkeys) (1995)" ...

**Source**

http://grouplens.org/datasets/movielens/latest/
PPLclass  
*Popularity based model.*

**Description**

Container for the model learned by an unpersonalized popularity-based algorithm.

**Slots**

- `alg`: The algorithm denominator, of class "character".
- `data`: the dataset used for training the model, class "matrix".
- `indices`: the indices of items ordered by popularity, class "integer".
- `parameters`: the parameters used in the model, class "list".

**Methods**

`show` signature(object = "PPLclass")

**See Also**

[rrecsys](#).

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predict  
*Generate predictions.*

**Description**

Generate predictions on any of the previously trained models.

**Arguments**

- `model`: A previously trained model, see [rrecsys](#).
- `round`: object of class "logical", if `TRUE` all the predictions are rounded to integer values, else values are returned as calculated.

**Value**

All unrated items are predicted and the entire matrix is returned with the new ratings.

**See Also**

[rrecsys](#), [IBclass](#), [SVDclass](#).
Example

data("mlLatest100k")
smallML <- mlLatest100k[1:50, 1:100]
exExpl <- defineData(smallML)
modelExp <- rrecsys(exExpl, alg = "funk", k = 10, learningRate = 0.01, regCoef = 0.001)
pre1 <- predict(modelExp, Round = TRUE)

<table>
<thead>
<tr>
<th>rankScore</th>
<th>Rank Score</th>
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</table>

Description

Rank Score extends the recall metric to take the positions of correct items in a ranked list into
account.

Usage

rankScore(recommendedIDX, testSetIDX, alpha)

Arguments

- recommendedIDX: indices of the recommended items. Object of class numeric.
- testSetIDX: indices of the items in the test set. Object of class numeric
- alpha: is the ranking half life. Object of class numeric.

Details

Rank Score is defined as the ratio of the Rank Score of the correct items to best theoretical Rank
Score achievable for the user:

\[
rankscore_p = \sum_{i \in h} 2^{-\frac{\text{rank}(i) - 1}{\alpha}}
\]

\[
rankscore_{max} = \sum_{i=1}^{\left| T \right|} 2^{-\frac{i-1}{\alpha}}
\]

\[
rankscore = \frac{rankscore_p}{rankscore_{max}}
\]
Recommend

Generate recommendation.

Description

This method generates top-n recommendations based on a model that has been trained before. Two main methods: recommendHPR, recommendMF. The first method recommends the highest predicted ratings on a user. Instead recommendMF (currently available only for IBKNN and UBKNN), recommends the most frequent item in the user’s neighborhood.

Usage

recommendHPR(model, topN = 3)
recommendMF(model, topN = 3, pt)

Arguments

- **model**: the trained model of any algorithm.
- **topN**: number of items to be recommended per user, class numeric.
- **pt**: positive threshold, class numeric.

Value

Returns a list with suggested items for each user.

See Also

rrecsys.

Examples

```r
myratings <- matrix(sample(c(0:5), size = 200, replace = TRUE,
                           prob = c(.6,.08,.08,.08,.08,.08)), nrow = 20, byrow = TRUE)

myratings <- defineData(myratings)

r <- rrecsys(myratings, alg = "FunkSVD", k = 2)

rec <- recommendHPR(r)
```
Description

Based on the specific given algorithm a recommendation model will be trained.

Usage

rrecsys(data, alg, ...)

Arguments

data : Training set of class "matrix". The columns correspond to items and the rows correspond to users.
alg : A "character" string specifying the recommender algorithm to apply on the data.
... : other attributes, see details.

Details

Based on the value of `alg` the attributes will have different names and values. Possible configuration of `alg` and its meaning:

1. **itemAverage**. When `alg = "itemAverage"` the average rating of an item is used to make predictions and recommendations.

2. **userAverage**. When `alg = "userAverage"` the average rating of a user is used to make predictions and recommendations.

3. **globalAverage**. When `alg = "globalAverage"` the overall average of all ratings is used to make predictions and recommendations.

4. **Mostpopular**. The most popular algorithm ( `alg = "mostpopular"`) is the most simple algorithm for recommendations. Item will be ordered based on the number of times that they were rated. Recommendations for a particular user will be the most popular items from the data set which are not contained in the user’s training set.

5. **IBKNN**. As `alg = "IBKNN"` a k-nearest neighbor item-based collaborative filtering algorithm. Given two items `a` and `b`, we consider them as rating vectors \( \vec{a} \) and \( \vec{b} \). If the argument `simFunct` is set to "cos" the method computes the cosine similarity as:

\[
sim(\vec{a}, \vec{b}) = \cos(\vec{a}, \vec{b}) = \frac{\vec{a} \cdot \vec{b}}{|\vec{a}| \cdot |\vec{b}|}
\]

If the argument `simFunct` is set to "adjCos" the method determines the “adjusted cosine” distance among the items as:

\[
sim(\vec{a}, \vec{b}) = \sum_{u \in U} \frac{(r_{u,a} - \bar{r}_u) \cdot (r_{u,b} - \bar{r}_u)}{\sqrt{(r_{u,a} - \bar{r}_u)^2} \cdot \sqrt{(r_{u,b} - \bar{r}_u)^2}}
\]
It extracts, based on the value of the `neigh` attribute, the number of closest neighbors for each item.

6. **UBKNN**. As \texttt{alg = "UBKNN"} a k-nearest neighbor user-based collaborative filtering algorithm. Given two users $u$ and $v$, we consider them as rating vectors $\vec{u}$ and $\vec{v}$. If the argument `simFunct` is set to "cos" the method computes the cosine similarity as:

$$\text{sim}(\vec{u}, \vec{v}) = \frac{\vec{u} \cdot \vec{v}}{|\vec{u}| \times |\vec{v}|}$$

If the argument `simFunct` is set to "Pearson" the method determines the "Pearson correlation" among the users as:

$$\text{sim}(\vec{u}, \vec{v}) = \text{Pearson}(\vec{u}, \vec{v}) = \frac{\sum_{i \in I_u \cap I_v} (R_{ui} - \overline{R}_u)(R_{vi} - \overline{R}_v)}{\sqrt{\sum_{i \in I_u \cap I_v} (R_{ui} - \overline{R}_u)^2 \times \sum_{i \in I_u \cap I_v} (R_{vi} - \overline{R}_v)^2}}$$

It extracts, based on the value of the `neigh` attribute, the number of closest neighbors for each item.

7. **FunkSVD**. It implements \texttt{alg = "funkSVD"} a stochastic gradient descent optimization technique. The U(user) and V(item) factor matrices are initialized at small values and cropped to $k$ features. Each feature is trained until convergence (the convergence value has to be specified by the user, by configuring the `steps` argument). On each loop the algorithm predicts $r'_{ui}$ and calculates the error as:

$$r'_{ui} = u_u \ast v_i^T$$

$$e_{ui} = r_{ui} - r'_{ui}$$

The factors are updated:

$$v_{ik} \leftarrow v_{ik} + \text{learningRate} \ast (e_{ui} \ast u_{uk} - \text{regCoef} \ast v_{ik})$$

$$u_{uk} \leftarrow u_{uk} + \text{lambda} \ast (e_{ui} \ast v_{ik} - \gamma \ast u_{uk})$$

. The attribute `learningRate` represents the learning rate, while `regCoef` corresponds to the weight of the regularization term. If the argument `biases` is TRUE, the biases will be computed to update the features and generate predictions.

8. **wALS**. The \texttt{alg = "wALS"} weighted Alternated Least squares method. For a given non-negative weight matrix $W$ the algorithm will perform updates on the item $V$ and user $U$ feature matrix as follows:

$$U_i = R_i \ast \tilde{W}_i \ast V \ast (V^T \ast \tilde{W}_i \ast V + \text{lambda} \times \sum_j W_{ij})^{-1}$$

$$V_j = R_j^T \ast \tilde{W}_j \ast U \ast (V^T \ast \tilde{W}_j \ast U + \text{lambda} \times \sum_i W_{ij})^{-1}$$

Initially the $V$ matrix is initialized with Gaussian random numbers with mean zero and small standard deviation. Than $U$ and $V$ are updated until convergence. The attribute `scheme` must specify the scheme(uni, uo, io, co) to use.
9. **BPR.** In this implementation of BPR (alg = "BPR") is applied a stochastic gradient descent approach that randomly choose triples from $D_R$ and trains the model $\Theta$. In this implementation the BPR optimization criterion is applied on matrix factorization. If $R = U \times V^T$, where $U$ and $V$ are the usual feature matrix cropped to $k$ features, the parameter vector of the model is $\Theta = (U, V)$. The Boolean randomInit parameter determines whatever the feature matrix are initialized to a random value or at a static 0.1 value. The algorithm will use three regularization terms, RegU for the user features $U$, RegI for positive updates and RegJ for negative updates of the item features $V$, lambda is the learning rate, autoConvergence is a toggle to the auto convergence validation, convergence upper limit to the convergence, and updateJ if true updates negative item features.

10. **SlopeOne** The Weighted Slope One (alg = "slopeone") performs prediction for a missing rating $\hat{r}_{ui}$ for user $u$ on item $i$ as the following average:

$$\hat{r}_{ui} = \frac{\sum_{\forall r_{uj}} (dev_{ij} + r_{uj}) c_{ij}}{\sum_{\forall r_{uj}} c_{ij}}.$$  

The average deviation rating $dev_{ij}$ between co-rated items is defined by:

$$dev_{ij} = \sum_{\forall u \in \text{users}} r_{ui} - r_{uj} \frac{c_{ij}}{c_{ij}}.$$  

Where $c_{ij}$ is the number of co-ratings between items $i$ and $j$ and $r_{ui}$ is an existing rating for user $u$ on item $i$. The Weighted Slope One takes into account both, information from users who rated the same item and the number of observed ratings.

To view a full list of available algorithms and their default configuration execute `rrecsysregistry`.

**Value**

Depending on the alg value it will be either an object of type **SVdclass** or **IBclass**.

**References**


Examples

```r
myratings <- matrix(sample(c(0:5), size = 200, replace = TRUE, prob = c(0.6, 0.08, 0.08, 0.08, 0.08)), nrow = 20, byrow = TRUE)
myratings <- defineData(myratings)
r <- rrcsys(myratings, alg = "funkSVD", k = 2)
r2 <- rrcsys(myratings, alg = "IBKNN", simFunct = "cos", neigh = 5)
rrecsysRegistry$get_entries()
```

```r
setStoppingCriteria
```

setStoppingCriteria  Set stopping criteria.

Description

Define stopping criteria for functions that need a convergence check.

Usage

```r
setStoppingCriteria(autoConverge = FALSE,
deltaErrorThreshold = 1e-05, nrloops = NULL, minNrLoops = 10)
```

Arguments

- `autoConverge`  class "logical", turns on the auto-convergence algorithm.
- `deltaErrorThreshold`  class "numeric", is the threshold for the auto-convergence algorithm.
- `nrLoops`  class "numeric", number of loops that will be performed in case autoConvergence is FALSE
- `minNrLoops`  class "numeric", the minimum number of loops to consider before verifying the deltaErrorThreshold.

Details

If `autoConvergence = TRUE` tells the package to monitor the difference of global RMSE on two consecutive iterations, and to see if it drops below a threshold value. Whenever it drops under the specified value the iteration is considered converged. If `FALSE` the limit of iterations is delimited by `nrLoops`
Methods

showStoppingCriteria Print on console the current configuration of the convergence algorithm.
showDeltaError Report the delta error on each iteration of the algorithm that requires an auto-convergence algorithm.

References


See Also

See Also as rrecsys, SVDclass, wALSclass, BPRclass.

Examples

```r
setStoppingCriteria(autoConverge = TRUE)
setStoppingCriteria(nrLoops = 30)
```

---

`slopeOneClass` *Slope One model.*

Description

Container for the model learned using Slope One algorithm.

Slots

alg: The algorithm denominator, of class "character".

data: the dataset used for training the model, class "matrix".

devcard: Deviation and Cardinality between columns, class "list".

Methods

show signature(object = "SVDclass")

See Also

rrecsys.
sparseDataSet-class  Dataset class for tuples (user, item, rating).

Description

Container for a sparse dataset that distinguishes between binary and non-binary feedback datasets. Data are stored as tuples (user, item, rating). Extends _ds.

Slots

data: the dataset, class "matrix".

binary: class "logical", determines if the item dataset contains binary (i.e. 1/0) or non-binary ratings.

minimum: class "numeric", defines the minimal value present in the dataset.

maximum: class "numeric", defines the maximal value present in the dataset.

intScale: object of class "logical", if TRUE the range of ratings in the dataset contains as well half star values.

userId: class "numeric", array containing all user IDs.

itemId: class "numeric", array containing all item IDs.

userPointers: class "list", pointer to all users position in the dataset.

itemPointers: class "list", pointer to all items position in the dataset.

Methods

nrow  signature(object = "sparseDataSet"): number of rows of the dataset.

ncol  signature(object = "sparseDataSet"): number of columns of the dataset.

dim  signature(object = "sparseDataSet"): returns the dimensions of the dataset.

rowRatings  signature(object = "sparseDataSet"): returns the number of ratings on each row.

colRatings  signature(object = "sparseDataSet"): returns the number of ratings on each column.

numRatings  signature(object = "sparseDataSet"): returns the total number of ratings.

[  signature(x = "sparseDataSet", i = "ANY", j = "ANY", drop = "ANY"): returns a subset of the dataset.

coerce  signature(from = "sparseDataSet", to = "matrix")

rowAverages  signature(object = "sparseDataSet"): returns the average rating on each row.

colAverages  signature(object = "sparseDataSet"): returns the average rating on each column.
Description

Container for the model learned using any matrix factorization algorithm.

Slots

- `alg`: The algorithm denominator, of class "character".
- `data`: the dataset used for training the model, class "matrix".
- `factors`: user(U) and items(V) factors, class "list".
- `parameters`: the parameters used in the model, class "list".
- `baselines`: Global, user and item baselines, class "list".

Methods

- `show` signature(object = "SVDclass")

See Also

- `rrecsys`.

Description

Container for the model learned using any k-nearest neighbor item-based collaborative filtering algorithm.

Slots

- `alg`: The algorithm denominator, of class "character".
- `data`: the dataset used for training the model, class "matrix".
- `sim`: The item - item similarity matrix, class "matrix".
- `sim_index_kNN`: The index of the k nearest neighbors for each item, class "matrix".
- `parameters`: the parameters used in the model, class "list".

Methods

- `show` signature(object = "UBclass")

See Also

- `rrecsys`.
wALSclass  
*Weighted Alternating Least Squares based model.*

**Description**

Container for the model learned using any weighted Alternating Least Squares based algorithm.

**Slots**

- **alg**: The algorithm denominator, of class "character".
- **data**: the dataset used for training the model, class "matrix".
- **factors**: user(U) and items(V) factors, class "list".
- **weightscheme**: The weighting scheme used in updating the factors, class "matrix".
- **parameters**: the parameters such as number of factors k, learning rate lambda, number of iterations until convergence and the weighting scheme) used in the model, class "list".

**Methods**

- **show** signature(object = "wALSclass")

**See Also**

*rrecsys.*

_ds-class  
*Dataset class.*

**Description**

Defines a structure for a dataset that distinguishes between binary and non-binary feedback datasets.

**Slots**

- **binary**: class "logical", determines if the item dataset contains binary (i.e. 1/0) or non-binary ratings.
- **minimum**: class "numeric", defines the minimal value present in the dataset.
- **maximum**: class "numeric", defines the maximal value present in the dataset.
- **intScale**: object of class "logical", if TRUE the range of ratings in the dataset contains as well half star values.

**Methods**

- **show** signature(object = "_ds")
- **sparsity** signature(object = "_ds"): returns the sparsity of the dataset.
- **summary** signature(object = "_ds"): summary of the characteristics of the dataset.
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