irspack

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BASIC TUTORIALS

irspack is a collection of recommender system algorithms for implicit feedback data.

Currently, in my opinion, there is no all-purpose algorithm for the recommendation tasks with implicit-feedback. So the key is to try out different algorithms, evaluate its performance against validation dataset, and optimize their performance by tuning hyperparameters. irspack is built to make this procedure easy for you.

Notable features include:

- optuna-backed, efficient hyperparameter optimization. In particular, pruning is used to speed-up the parameter search for several algorithms.
- Implementation of several parallelizable algorithms with Pybind11 and Eigen. Evaluation of recommenders' performance (which involves score-sorting and ranking metric computation) can be also done efficiently using these technologies.

CHAPTER

ONE

INSTALLATION

If you have a standard Python environment on MacOS/Linux, you can install the library from PyPI using pip:

```
pip install irspack
```

The binaries on PyPI have been built to use AVX instruction. If you want to use AVX2/AVX512 or your environment does not support AVX (e.g. Rosetta2 on Apple Silicon), install it from source by e.g., :

```
CFLAGS="-march=native" pip install git+https://github.com/tohtsky/irspack.git
```

1.1 Train our first movie recommender

In this tutorial, we build our first recommender system using a simple algorithm called P3alpha.

We will learn

- How to represent the implicit feedback dataset as a sparse matrix.
- How to fit `irspack`'s models using the sparse matrix representation.
- How to make a recommendation using our API.

[1]:
```
import numpy as np
import scipy.sparse as sps

from irspack.dataset import MovieLens1MDataManager
from irspack import P3alphaRecommender
```

1.1.1 Read Movielens 1M dataset

We first load the Movielens1M dataset. For the first time, you will be asked to allow downloading the dataset.

[2]:
```
loader = MovieLens1MDataManager()

df = loader.read_interaction()
df.head()
```

[2]:

	userId	movieId	rating	timestamp
0	1	1193	5	2000-12-31 22:12:40
1	1	661	3	2000-12-31 22:35:09
2	1	914	3	2000-12-31 22:32:48

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```
3       1     3408       4 2000-12-31 22:04:35
4       1     2355       5 2001-01-06 23:38:11
```

`df` stores the users' watch event history.

Although the rating information is available in this case, we will not be using this column. What matters to implicit feedback based recommender system is "which user interacted with which item (movie)".

By `loader` we can also read the dataframe for the movie meta data:

[3]:
```
movies = loader.read_item_info()
movies.head()
```

[3]:
```
                                    title                        genres  \
movieId
1                        Toy Story (1995)   Animation|Children's|Comedy
2                          Jumanji (1995)  Adventure|Children's|Fantasy
3                 Grumpier Old Men (1995)                Comedy|Romance
4                Waiting to Exhale (1995)                  Comedy|Drama
5       Father of the Bride Part II (1995)                        Comedy

         release_year
movieId
1                1995
2                1995
3                1995
4                1995
5                1995
```

1.1.2 Represent your data as a sparse matrix

We represent the data as a sparse matrix X, whose element X_{ui} is given by

$$X_{ui} = \begin{cases} 1 & \text{if the user } u \text{ has watched the item (movie) } i \\ 0 & \text{otherwise} \end{cases}$$

For this purpose, we use `np.unique` function with `return_inverse=True`. This will return a tuple that consists of

1. The list of unique user/movie ids appearing in the original user/movie id array
2. How the original user/movie id array elements are mapped to the array 1.

So if we do

[4]:
```
unique_user_ids, user_index = np.unique(df.userId, return_inverse=True)
unique_movie_ids, movie_index = np.unique(df.movieId, return_inverse=True)
```

then `unique_user_ids[user_index]` and `unique_movie_ids[movie_index]` is equal to the original array:

[5]:
```
assert np.all( unique_user_ids[user_index] == df.userId.values )
assert np.all( unique_movie_ids[movie_index] == df.movieId.values )
```

Thus, we can think of `user_index` and `movie_index` as representing the row and column positions of non-zero elements, respectively.

Now X can be constructed as scipy's sparse csr matrix as follows.

[6]:
```
X = sps.csr_matrix(
    (
        np.ones(df.shape[0]), # values of non-zero elements
        (
            user_index, # rows of non-zero elements
            movie_index # cols of non-zero elements
        )
    )
)

X
```

[6]:
```
<6040x3706 sparse matrix of type '<class 'numpy.float64'>'
        with 1000209 stored elements in Compressed Sparse Row format>
```

We encounter this pattern so often, so there is `df_to_sparse` function in irspack:

[7]:
```
from irspack import df_to_sparse
X_, unique_user_ids_, unique_item_ids_ = df_to_sparse(df, 'userId', 'movieId')

# X_ is identitcal to X.
assert (X_ - X).getnnz() == 0
```

1.1.3 Fit the recommender.

We fit `P3alphaRecommender` against X.

[8]:
```
recommender = P3alphaRecommender(X)
recommender.learn()
```

[8]:
```
<irspack.recommenders.p3.P3alphaRecommender at 0x7f61e7e679d0>
```

1.1.4 Check the recommender's output

Suppose there is a new user who has just watched "Toy Story". Let us see what would be the recommended for this user.

We first represent the user's watch profile as another sparse matrix (which contains a single non-zero element).

[9]:
```
movie_id_vs_movie_index = { mid: i for i, mid in enumerate(unique_movie_ids)}

toystory_id = 1
toystory_watcher_matrix = sps.csr_matrix(
    ([1], ([0], [movie_id_vs_movie_index[toystory_id]])),
    shape=(1, len(unique_movie_ids)) # this time shape parameter is required
)

movies.loc[toystory_id]
```

[9]:
```
title                        Toy Story (1995)
genres          Animation|Children's|Comedy
release_year                            1995
Name: 1, dtype: object
```

Since this user is new (previously unseen) to the recommender, we use `get_score_cold_user_remove_seen` method.

`remove_seen` means that we mask the scores for the items that user had watched already (in this case, Toy Story) so that such items would not be recommended again.

As you can see, the score corresponding to "Toy Story" has $-\infty$ score.

[10]:
```
score = recommender.get_score_cold_user_remove_seen(
    toystory_watcher_matrix
)

# Id 1 (index 0) is masked (have -infinity score)
score
```

[10]:
```
array([[          -inf, 8.18606963e-04, 4.30083199e-04, ...,
        4.30589311e-05, 1.09994485e-05, 2.71571993e-04]])
```

To get the recommendation, we `argsort` wthe score by descending order and convert "movie index" (which starts from 0) to "movie id".

[11]:
```
recommended_movie_index = score[0].argsort()[::-1][:10]
recommended_movie_ids = unique_movie_ids[recommended_movie_index]

# Top-10 recommendations
recommended_movie_ids
```

[11]:
```
array([2858, 1265, 2396, 3114,  260, 1210, 1196, 1270, 2028,   34])
```

And here are the titles of the recommendations.

[12]:
```
movies.reindex(recommended_movie_ids)
```

[12]:
```
                                                    title  \
movieId
2858                                American Beauty (1999)
1265                                  Groundhog Day (1993)
2396                              Shakespeare in Love (1998)
3114                                    Toy Story 2 (1999)
260              Star Wars: Episode IV - A New Hope (1977)
1210     Star Wars: Episode VI - Return of the Jedi (1983)
1196     Star Wars: Episode V - The Empire Strikes Back...
1270                               Back to the Future (1985)
2028                              Saving Private Ryan (1998)
34                                             Babe (1995)

                                       genres  release_year
movieId
2858                            Comedy|Drama          1999
1265                          Comedy|Romance          1993
2396                          Comedy|Romance          1998
3114             Animation|Children's|Comedy          1999
260            Action|Adventure|Fantasy|Sci-Fi          1977
1210     Action|Adventure|Romance|Sci-Fi|War          1983
1196       Action|Adventure|Drama|Sci-Fi|War          1980
1270                            Comedy|Sci-Fi          1985
```

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```
2028                          Action|Drama|War          1998
34                   Children's|Comedy|Drama          1995
```

The above pattern - mapping item IDs to indexes, creating sparse matrices, and reverting indexes of recommended items to item IDs - is a quite common one, and we have also created a convenient class that does the item index/ID mapping:

[13]:
```
from irspack.utils.id_mapping import ItemIDMapper

id_mapper = ItemIDMapper(
    item_ids=unique_movie_ids
)
id_and_scores = id_mapper.recommend_for_new_user(
    recommender,
    [toystory_id], cutoff = 10
)
movies.reindex(
    [ item_id for item_id, score in id_and_scores ]
)
```

[13]:
```
                                                  title  \
movieId
2858                                American Beauty (1999)
1265                                  Groundhog Day (1993)
2396                              Shakespeare in Love (1998)
3114                                      Toy Story 2 (1999)
260              Star Wars: Episode IV - A New Hope (1977)
1210     Star Wars: Episode VI - Return of the Jedi (1983)
1196     Star Wars: Episode V - The Empire Strikes Back...
1270                               Back to the Future (1985)
2028                              Saving Private Ryan (1998)
34                                             Babe (1995)

                                       genres  release_year
movieId
2858                             Comedy|Drama          1999
1265                           Comedy|Romance          1993
2396                           Comedy|Romance          1998
3114              Animation|Children's|Comedy          1999
260           Action|Adventure|Fantasy|Sci-Fi          1977
1210     Action|Adventure|Romance|Sci-Fi|War          1983
1196       Action|Adventure|Drama|Sci-Fi|War          1980
1270                            Comedy|Sci-Fi          1985
2028                          Action|Drama|War          1998
34                   Children's|Comedy|Drama          1995
```

While the above result might make sense, this is not an optimal result. To get better results, we have to tune the recommender's hyper parameters against some accuracy metric measured on a validation set.

In the next tutorial, we will see how to define the hold-out and validation score.

1.2 Evaluation of recommender systems

In this tutorial, we explain how to evaluate recommender systems with implicit feedback by holding out method.

[1]:
```
from irspack.dataset import MovieLens1MDataManager
from irspack import (
    P3alphaRecommender, TopPopRecommender,
    rowwise_train_test_split, Evaluator,
    df_to_sparse
)
```

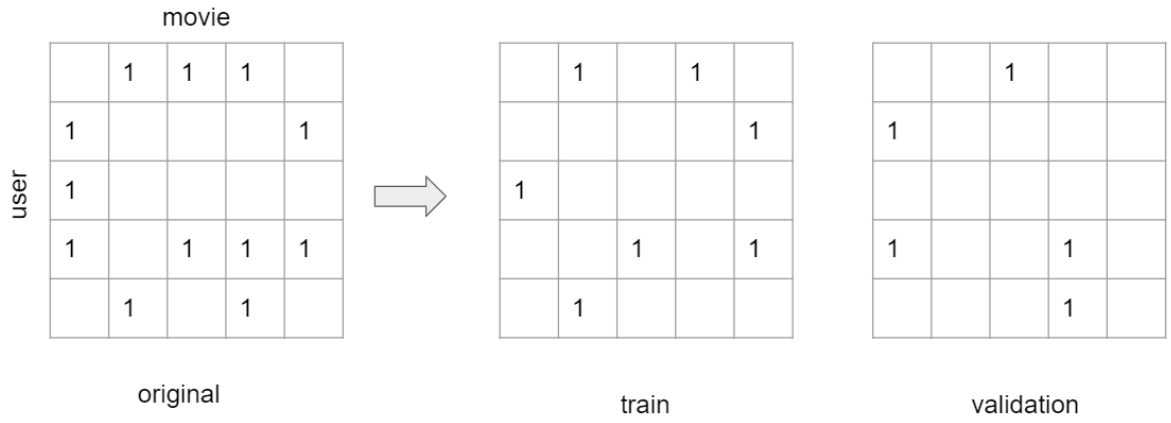
1.2.1 Read the ML1M dataset again.

As in the previous tutorial, we load the rating dataset and construct a sparse matrix.

[2]:
```
loader = MovieLens1MDataManager()

df = loader.read_interaction()

X, unique_user_ids, unique_movie_ids = df_to_sparse(
    df, 'userId', 'movieId'
)
```

1.2.2 Split scheme 1. Hold-out for all users.

To evaluate the performance of a recommender system trained with implicit feedback, the standard method is to hide some subset of the known user-item interactions as a validation set and see how the recommender ranks these hidden groundtruths:



We have prepared a fast implementaion of such a split (with random selection of these subset) in `rowwise_train_test_split` function:

[3]:
```
X_train, X_valid = rowwise_train_test_split(X, test_ratio=0.2, random_state=0)

assert X_train.shape == X_valid.shape
```

They sum back to the original matrix:

[4]:
```
X - (X_train + X_valid) # 0 stored elements
```

[4]:
```
<6040x3706 sparse matrix of type '<class 'numpy.float64'>'
        with 0 stored elements in Compressed Sparse Row format>
```

There is no overlap of non-zero elements:

[5]:
```
X_train.multiply(X_valid) # Element-wise multiplication yields 0 stored elements
```

[5]:
```
<6040x3706 sparse matrix of type '<class 'numpy.float64'>'
        with 0 stored elements in Compressed Sparse Row format>
```

This scheme however has a problem regarding the performance because we have to compute the recommendation score for all the users. So in the next tutorial, we will be using a sub-sampled version of this splitting.

1.2.3 Obtain the evaluation metric

Now we define the `Evaluator` object, which will measure the performance of various recommender systems based on `X_valid` (the meaning of `offset=0` will be clarified in the next tutorial).

[6]:
```
evaluator = Evaluator(X_valid, offset=0)
```

We fit `P3alphaRecommender` using `X_train`, and compute its accuracy metrics against `X_valid` using `evaluator`.

Internally, `evaluator` calls the recommender's `get_score_remove_seen` method, sorts the score to obtain the rank, and reconciles it with the stored validation interactions.

[7]:
```
recommender = P3alphaRecommender(X_train, top_k=100)
recommender.learn()

evaluator.get_scores(recommender, cutoffs=[5, 10])
```

[7]:
```
OrderedDict([('hit@5', 0.7988410596026491),
             ('recall@5', 0.09333713653053713),
             ('ndcg@5', 0.396153990817333),
             ('map@5', 0.06632471989643292),
             ('precision@5', 0.37317880794701996),
             ('gini_index@5', 0.9738255665593293),
             ('entropy@5', 4.777123828102488),
             ('appeared_item@5', 536.0),
             ('hit@10', 0.8925496688741722),
             ('recall@10', 0.15053594583416965),
             ('ndcg@10', 0.3662089065311077),
             ('map@10', 0.08982972949880254),
             ('precision@10', 0.32049668874172194),
             ('gini_index@10', 0.961654047669253),
             ('entropy@10', 5.1898345912683315),
             ('appeared_item@10', 764.0)])
```

1.2.4 Comparison with a simple baseline

Now that we have a qualitative way to measure the recommenders' performance, we can compare the performance of different algorithms.

As a simple baseline, we fit `TopPopRecommender`, which recommends items with descending order of the popularity in the train set, regardless of the users' watch event history. (But note that already-seen items by a user will not be commended again).

[8]:
```
toppop_recommender = TopPopRecommender(X_train)
toppop_recommender.learn()

evaluator.get_scores(toppop_recommender, cutoffs=[5, 10])
```

[8]:
```
OrderedDict([('hit@5', 0.5473509933774835),
             ('recall@5', 0.04097159018092859),
             ('ndcg@5', 0.21914854330480912),
             ('map@5', 0.025239375245273265),
             ('precision@5', 0.20884105960264907),
             ('gini_index@5', 0.9972226173414867),
             ('entropy@5', 2.608344593727912),
             ('appeared_item@5', 42.0),
             ('hit@10', 0.6637417218543047),
             ('recall@10', 0.0667908851617647),
             ('ndcg@10', 0.19939297384808613),
             ('map@10', 0.033298013667913656),
             ('precision@10', 0.17811258278145692),
             ('gini_index@10', 0.9950046639957398),
             ('entropy@10', 3.1812807131889786),
             ('appeared_item@10', 69.0)])
```

So we see that `P3alphaRecommender` actually exhibits better accuracy scores compared to rather trivial `TopPopRecommender`.

In the next tutorial, we will optimize the recommender's performance using the hold-out method.

1.3 Hyperparameter Optimization

In this tutorial, we first demonstrate how `P3alphaRecommender`'s performance can be optimized by optuna-backed `tune` function.

Then, by further splitting the ground-truth interaction into tran, validation and test ones, we compare several recommenders' performance optimized on the validation set and measured on the test set.

[1]:
```
from IPython.display import clear_output, display
import numpy as np
import scipy.sparse as sps
from sklearn.model_selection import train_test_split

from irspack.dataset import MovieLens1MDataManager
from irspack import (
    P3alphaRecommender, rowwise_train_test_split, Evaluator,
    df_to_sparse
)
```

1.3.1 Read the ML1M dataset again.

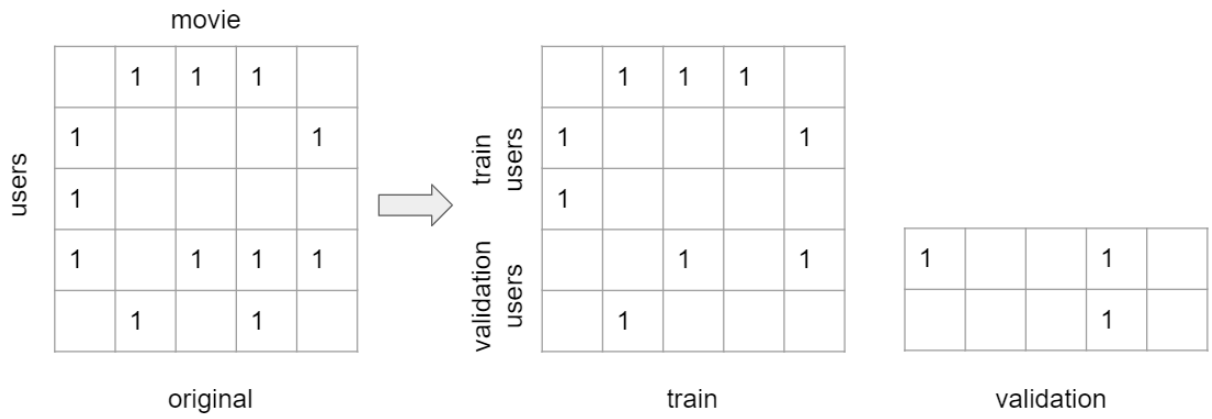
We again prepare the sparse matrix `X`.

[2]:
```
loader = MovieLens1MDataManager()

df = loader.read_interaction()

movies = loader.read_item_info()
movies.head()


X, unique_user_ids, unique_movie_ids = df_to_sparse(
    df, 'userId', 'movieId'
)
```

1.3.2 Split scheme 2. Hold-out for partial users.

To perform the hyperparameter optimization, we have to repeatedly measure the accuracy metrics on the validation set. As mentioned in the previous tutorial, doing this for all users is time-comsuming (often heavier than the recommender's learning process), so we truncate this subset as follows:

1. First split **users** into "train", "validation" (and "test") ones.
2. For train users, feed all their interactions into the recommender. For validation (test) users, hold-out part of their interaction for the validation ("prediction" part), and feed the rest ("learning" part) into the recommender.
3. After the fit, ask the recommender to output the score only for validation (test) users, and see how it ranks these held-out interactions for the validation (test) users.



Although we have prepared another function to do this procedure, let us first do this manually.

[3]:
```
# Split users into train and validation users.

X_train_user, X_valid_user = train_test_split(X, test_size=.4, random_state=0)

# Split the validation users' interaction into learning 50% and predcition 50%.

X_valid_learn, X_valid_predict = rowwise_train_test_split(
```

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```
    X_valid_user, test_ratio=.5, random_state=0
)
```

1.3.3 Define the evaluator and optimize the validation metric

As illustrated above, we will use

- Train users' all interactions (`X_train_user`)
- Validation users' 50% interaction (`X_valid_learn`)

as the recommender's training resource, and validation users' rest interaction (`X_valid_predict`) as the held-out ground truth:

[4]:
```
X_train_val_learn = sps.vstack([X_train_user, X_valid_learn])
evaluator = Evaluator(X_valid_predict, offset=X_train_user.shape[0], target_metric='ndcg
↪', cutoff=20)
```

The `offset` parameter specifies where the validation user block begins (where the train user block ends).

Now to start the optimization.

[5]:
```
best_params, validation_results = P3alphaRecommender.tune(X_train_val_learn, evaluator,␣
↪random_seed=0, n_trials=20)
clear_output() # output is a bit lengthy
```

The best `ndcg@20` value is

[6]:
```
validation_results['ndcg@20'].max()
```

[6]:
```
0.5159628863136182
```

which has been obtained by using these hyper parameters:

[7]:
```
best_params
```

[7]:
```
{'top_k': 217, 'normalize_weight': True}
```

Meanwhile, the default argument of `P3alphaRecommdner` (which has been used so far) attains `ndcg@20` = 0.4084. So this is indeed a significant improvement:

[8]:
```
rec_default = P3alphaRecommender(X_train_val_learn).learn()
evaluator.get_score(rec_default)['ndcg']
```

[8]:
```
0.4084060191998281
```

1.3.4 Check the recommender's output again

Let us check how our recommender has evolved from the first tutorial. We consider the same setting (a new user has watched "Toy Story"), but fit the recommender using the obtained parameters.

[9]:
```
rec_tuned = P3alphaRecommender(X, **best_params).learn()

from irspack import ItemIDMapper
id_mapper = ItemIDMapper(unique_movie_ids)
```

[10]:
```
toystory_id = 1
recommended_id_and_score = id_mapper.recommend_for_new_user(
    rec_tuned, user_profile=[toystory_id], cutoff=10
)

# Top-10 recommendations
movies.reindex([movie_id for movie_id, score in recommended_id_and_score])
```

[10]:

movieId	title	genres	release_year
1265	Groundhog Day (1993)	Comedy|Romance	1993
2396	Shakespeare in Love (1998)	Comedy|Romance	1998
3114	Toy Story 2 (1999)	Animation|Children's|Comedy	1999
1270	Back to the Future (1985)	Comedy|Sci-Fi	1985
2028	Saving Private Ryan (1998)	Action|Drama|War	1998
34	Babe (1995)	Children's|Comedy|Drama	1995
2571	Matrix, The (1999)	Action|Sci-Fi|Thriller	1999
356	Forrest Gump (1994)	Comedy|Romance|War	1994
2355	Bug's Life, A (1998)	Animation|Children's|Comedy	1998
1197	Princess Bride, The (1987)	Action|Adventure|Comedy|Romance	1987

Note how drastically the recommended contents have changed (increased significance of genre "Children's" and disapperance of "Star Wars" series, etc…).

1.3.5 A train/validation/test split example

To rigorously compare the performance of various recommender algorithms, we should measure the final score against the **test** dataset, not the validation set, and it is straightforward now.

To begin with, we have prepared a function called `split_dataframe_partial_user_holdout` which splits the users in the original dataframe into train/validation/test users, holding out partial interaction for validation/test user:

[11]:
```
from irspack.split import split_dataframe_partial_user_holdout

dataset, item_ids = split_dataframe_partial_user_holdout(
    df, 'userId', 'movieId', val_user_ratio=.3, test_user_ratio=.3,
    heldout_ratio_val=.5, heldout_ratio_test=.5
)

dataset
```

[11]:
```
{'train': <irspack.split.userwise.UserTrainTestInteractionPair at 0x7ff61f483430>,
 'val': <irspack.split.userwise.UserTrainTestInteractionPair at 0x7ff61f4831f0>,
 'test': <irspack.split.userwise.UserTrainTestInteractionPair at 0x7ff61f482bc0>}
```

As you can see, the returned `dataset` is a dictionary which stores train/validation/test-users' interactions as an instance of `UserTrainTestInteractionPair`.

[12]:
```
train_users = dataset['train']
val_users = dataset['val']
test_users = dataset['test']

# Concatenate train/validation users into one.
train_and_val_users = train_users.concat(val_users)
```

[13]:
```
val_users.X_train
```

[13]:
```
<1812x3706 sparse matrix of type '<class 'numpy.float64'>'
        with 152333 stored elements in Compressed Sparse Row format>
```

[14]:
```
val_users.X_test
```

[14]:
```
<1812x3706 sparse matrix of type '<class 'numpy.float64'>'
        with 151435 stored elements in Compressed Sparse Row format>
```

[15]:
```
val_users.X_all # which equals val_users.X_train + val_users.X_test
```

[15]:
```
<1812x3706 sparse matrix of type '<class 'numpy.float64'>'
        with 303768 stored elements in Compressed Sparse Row format>
```

[16]:
```
# For train users, there is no "test" interaction held out.
train_users.X_test
```

[16]:
```
<2416x3706 sparse matrix of type '<class 'numpy.float64'>'
        with 0 stored elements in Compressed Sparse Row format>
```

For each recommender algorithm (here `P3alpha`, `RP3beta`, `IALS` and `DenseSLIM`), we perform:

1. Hyperparameter optimization. During this phase, we will be using train users' all interaction and validation users' train interaction as the source of learning, and validation users' test interaction as the held-out ground truth.

2. Evaluation. During this phase, we will include train/validation users' all interactions as well as test users' train interaction as the source of learning, and fit the model using the parameters obtained in the optimization phase. Then we measure the recommender's performance against **test** users' test interaction.

[17]:
```
from typing import Type
from irspack import DenseSLIMRecommender, RP3betaRecommender, IALSRecommender,␣
↪BaseRecommender
```

[18]:
```
val_evaluator = Evaluator(
    val_users.X_test,
    offset=train_users.n_users,
    cutoff=20, target_metric="ndcg"
)
test_evaluator = Evaluator(
    test_users.X_test,
    offset=train_and_val_users.n_users
)
test_results = []
recommender_name_vs_best_parameter = {}
recommender_class: Type[BaseRecommender]
for recommender_class in [IALSRecommender, DenseSLIMRecommender, P3alphaRecommender,␣
↪RP3betaRecommender]:
    print(f'Start tuning {recommender_class.__name__}.')
    best_params, validation_results_df = recommender_class.tune(
        sps.vstack([train_users.X_all, val_users.X_train]),
        val_evaluator, n_trials=40, random_seed=0
    )
    recommender = recommender_class(
        sps.vstack([train_and_val_users.X_all, test_users.X_train]),
        **best_params
    ).learn()
    recommender_name_vs_best_parameter[recommender_class.__name__] = best_params

    test_score = dict(
        algorithm=recommender_class.__name__,
        **test_evaluator.get_scores(recommender, cutoffs=[20])
    )
    test_results.append(test_score)
    clear_output()
```

As you can see below, iALS and DenseSLIM outperforms others in terms of accuracy measures (recall, ndcg, map).

iALS performed well regarding the diversity scores (entropy, gini-index, appeared_item), too.

[19]:
```
import pandas as pd
pd.DataFrame(test_results)
```

[19]:

	algorithm	hit@20	recall@20	ndcg@20	map@20	\
0	IALSRecommender	0.996137	0.208540	0.576164	0.135950	
1	DenseSLIMRecommender	0.995033	0.207463	0.572965	0.135436	
2	P3alphaRecommender	0.993377	0.182982	0.526259	0.114564	
3	RP3betaRecommender	0.995033	0.188152	0.537070	0.119353	

	precision@20	gini_index@20	entropy@20	appeared_item@20

(continues on next page)

(continued from previous page)

```
0      0.528201       0.915915    5.989211            1108.0
1      0.525055       0.926926    5.859120            1018.0
2      0.477152       0.962736    5.174319             690.0
3      0.486010       0.957136    5.297020             846.0
```

Let's ask each recommender, "What would you recommend to a user who has just seen "Toy Story"?

IALS, DenseSLIM, RP3beta rank "Toy Story2" at the top of recommendationlist, which seems appropriate.

[20]:
```
for recommender_class in [IALSRecommender, DenseSLIMRecommender, RP3betaRecommender,␣
↪P3alphaRecommender]:
    rec_tuned = recommender_class(X, **recommender_name_vs_best_parameter[recommender_
↪class.__name__]).learn()

    toystory_id = 1
    recommended_id_and_score = id_mapper.recommend_for_new_user(
        rec_tuned, user_profile=[toystory_id], cutoff=10
    )
    print(f"{recommender_class.__name__}'s result:")
    # Top-10 recommendations
    display(movies.reindex([movie_id for movie_id, score in recommended_id_and_score]))
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.HTML object>
```

```
IALSRecommender's result:
```

```
                              title                                genres  \
movieId
3114              Toy Story 2 (1999)          Animation|Children's|Comedy
34                       Babe (1995)              Children's|Comedy|Drama
2355            Bug's Life, A (1998)          Animation|Children's|Comedy
1265            Groundhog Day (1993)                        Comedy|Romance
588                   Aladdin (1992)  Animation|Children's|Comedy|Musical
2396      Shakespeare in Love (1998)                        Comedy|Romance
2321            Pleasantville (1998)                               Comedy
356              Forrest Gump (1994)                   Comedy|Romance|War
1148      Wrong Trousers, The (1993)                     Animation|Comedy
595      Beauty and the Beast (1991)         Animation|Children's|Musical

         release_year
movieId
3114             1999
34               1995
2355             1998
1265             1993
588              1992
2396             1998
2321             1998
356              1994
1148             1993
595              1991
```

```
DenseSLIMRecommender's result:
```

```
                                     title  \
movieId
3114                      Toy Story 2 (1999)
2355                    Bug's Life, A (1998)
34                             Babe (1995)
588                          Aladdin (1992)
1265                    Groundhog Day (1993)
2396               Shakespeare in Love (1998)
356                     Forrest Gump (1994)
1148               Wrong Trousers, The (1993)
1641                   Full Monty, The (1997)
1923     There's Something About Mary (1998)

                                      genres  release_year
movieId
3114              Animation|Children's|Comedy          1999
2355              Animation|Children's|Comedy          1998
34                    Children's|Comedy|Drama          1995
588       Animation|Children's|Comedy|Musical          1992
1265                         Comedy|Romance          1993
2396                         Comedy|Romance          1998
356                     Comedy|Romance|War          1994
1148                      Animation|Comedy          1993
1641                              Comedy          1997
1923                              Comedy          1998
```

RP3betaRecommender's result:

```
                                                 title  \
movieId
3114                                Toy Story 2 (1999)
1265                              Groundhog Day (1993)
2396                         Shakespeare in Love (1998)
34                                      Babe (1995)
2355                              Bug's Life, A (1998)
1270                          Back to the Future (1985)
260              Star Wars: Episode IV - A New Hope (1977)
2028                         Saving Private Ryan (1998)
356                                Forrest Gump (1994)
1210     Star Wars: Episode VI - Return of the Jedi (1983)

                                      genres  release_year
movieId
3114              Animation|Children's|Comedy          1999
1265                         Comedy|Romance          1993
2396                         Comedy|Romance          1998
34                    Children's|Comedy|Drama          1995
2355              Animation|Children's|Comedy          1998
1270                           Comedy|Sci-Fi          1985
260          Action|Adventure|Fantasy|Sci-Fi          1977
2028                       Action|Drama|War          1998
356                     Comedy|Romance|War          1994
1210     Action|Adventure|Romance|Sci-Fi|War          1983
```

```
P3alphaRecommender's result:
```

```
                            title                                genres  \
movieId
1265           Groundhog Day (1993)                        Comedy|Romance
2396     Shakespeare in Love (1998)                        Comedy|Romance
3114             Toy Story 2 (1999)          Animation|Children's|Comedy
1270      Back to the Future (1985)                          Comedy|Sci-Fi
2028     Saving Private Ryan (1998)                     Action|Drama|War
34                      Babe (1995)              Children's|Comedy|Drama
356             Forrest Gump (1994)                   Comedy|Romance|War
2355            Bug's Life, A (1998)          Animation|Children's|Comedy
1197     Princess Bride, The (1987)      Action|Adventure|Comedy|Romance
588                  Aladdin (1992)  Animation|Children's|Comedy|Musical

         release_year
movieId
1265             1993
2396             1998
3114             1999
1270             1985
2028             1998
34               1995
356              1994
2355             1998
1197             1987
588              1992
```

1.4 API References

1.4.1 Evaluators

Evaluator	Evaluates recommenders' performance against validation set.
EvaluatorWithColdUser	Evaluates recommenders' performance against cold (unseen) users.

irspack.evaluation.Evaluator

class irspack.evaluation.**Evaluator**(*ground_truth*, *offset=0*, *cutoff=10*, *target_metric='ndcg'*, *recommendable_items=None*, *per_user_recommendable_items=None*, *masked_interactions=None*, *n_threads=None*, *recall_with_cutoff=False*, *mb_size=128*)

Bases: `object`

Evaluates recommenders' performance against validation set.

Parameters

- **ground_truth** (*Union[scipy.sparse.csr_matrix, scipy.sparse.csc_matrix]*) – The ground-truth.

- **offset** (*int*) – Where the validation target user block begins. Often the validation set is defined for a subset of users. When offset is not 0, we assume that the users with validation ground truth corresponds to X_train[offset:] where X_train is the matrix feeded into the recommender class. Defaults to 0.
- **cutoff** (*int, optional*) – Controls the default number of recommendation. When the evaluator is used for parameter tuning, this cutoff value will be used. Defaults to 10.
- **target_metric** (*str, optional*) – Specifies the target metric when this evaluator is used for parameter tuning. Defaults to "ndcg".
- **recommendable_items** (*Optional[List[int]], optional*) – Global recommendable items. Defaults to None. If this parameter is not None, evaluator will be concentrating on the recommender's score output for these recommendable_items, and compute the ranking performance within this subset.
- **per_user_recommendable_items** (*Union[None, List[List[int]], csr_matrix, csc_matrix]*) – Similar to *recommendable_items*, but this time the recommendable items can vary among users. If a sparse matrix is given, its nonzero indices are regarded as the list of recommendable items. Defaults to *None*.
- **masked_interactions** (*Optional[csr_matrix]*) – If set, this matrix masks the score output of recommender model where it is non-zero. If none, the mask will be the training matrix itself owned by the recommender.
- **n_threads** (*Optional[int]*) – Specifies the Number of threads to sort scores and compute the evaluation metrics. If *None*, the environment variable `"IRSPACK_NUM_THREADS_DEFAULT"` will be looked up, and if the variable is not set, it will be set to `os.cpu_count()`. Defaults to *None*.
- **recall_with_cutoff** (*bool, optional*) – This affects the definition of recall. If `True`, for each user, recall will be computed as

$$\frac{N_{\text{hit}}}{\min(\text{cutoff}, N_{\text{ground truth}})}$$

  If `False`, this will be

$$\frac{N_{\text{hit}}}{N_{\text{ground truth}}}$$

- **mb_size** (*int, optional*) – The rows of chunked user score. Defaults to 1024.

__init__(*ground_truth*, *offset=0*, *cutoff=10*, *target_metric='ndcg'*, *recommendable_items=None*, *per_user_recommendable_items=None*, *masked_interactions=None*, *n_threads=None*, *recall_with_cutoff=False*, *mb_size=128*)

Parameters

- **ground_truth** (*Union[csr_matrix, csc_matrix]*) –
- **offset** (*int*) –
- **cutoff** (*int*) –
- **target_metric** (*str*) –
- **recommendable_items** (*Optional[List[int]]*) –
- **per_user_recommendable_items** (*Union[None, List[List[int]], csr_matrix, csc_matrix]*) –
- **masked_interactions** (*Optional[Union[csr_matrix, csc_matrix]]*) –

- **n_threads** (*Optional[int]*) –
- **recall_with_cutoff** (*bool*) –
- **mb_size** (*int*) –

Return type
None

Methods

__init__(ground_truth[, offset, cutoff, ...])	
get_score(model)	Compute the score with the cutoff being `self.cutoff`.
get_scores(model, cutoffs)	Compute the score with the specified cutoffs.
get_target_score(model)	Compute the optimization target score (self.target_metric) with the cutoff being `self.cutoff`.

Attributes

`n_users`
`n_items`
`masked_interactions`

get_score(*model*)

Compute the score with the cutoff being `self.cutoff`.

Parameters
model (BaseRecommender) – The evaluated recommender.

Returns
metric values.

Return type
Dict[str, float]

get_scores(*model*, *cutoffs*)

Compute the score with the specified cutoffs.

Parameters

- **model** (BaseRecommender) – The evaluated recommender.
- **cutoffs** (*List[int]*) – for each value in cutoff, the class computes the metric values.

Returns
The Resulting metric values. This time, the result will look like `{"ndcg@20": 0.35, "map@20": 0.2, ...}`.

Return type
Dict[str, float]

`get_target_score`(*model*)

Compute the optimization target score (self.target_metric) with the cutoff being `self.cutoff`.

Parameters
model (`BaseRecommender`) – The evaluated model.

Returns
The metric value.

Return type
float

irspack.evaluation.EvaluatorWithColdUser

`class irspack.evaluation.`**`EvaluatorWithColdUser`**(*input_interaction*, *ground_truth*, *cutoff=10*, *target_metric='ndcg'*, *recommendable_items=None*, *per_user_recommendable_items=None*, *masked_interactions=None*, *n_threads=None*, *recall_with_cutoff=False*, *mb_size=1024*)

Bases: *Evaluator*

Evaluates recommenders' performance against cold (unseen) users.

Parameters

- **input_interaction** (*Union[scipy.sparse.csr_matrix, scipy.sparse.csc_matrix]*) – The cold-users' known interaction with the items.
- **ground_truth** (*Union[scipy.sparse.csr_matrix, scipy.sparse.csc_matrix]*) – The held-out ground-truth.
- **offset** (*int*) – Where the validation target user block begins. Often the validation set is defined for a subset of users. When offset is not 0, we assume that the users with validation ground truth corresponds to X_train[offset:] where X_train is the matrix feeded into the recommender class.
- **cutoff** (*int, optional*) – Controls the number of recommendation. Defaults to 10.
- **target_metric** (*str, optional*) – Optimization target metric. Defaults to "ndcg".
- **recommendable_items** (*Optional[List[int]], optional*) – Global recommendable items. Defaults to None. If this parameter is not None, evaluator will be concentrating on the recommender's score output for these recommendable_items, and compute the ranking performance within this subset.
- **per_user_recommendable_items** (*Optional[List[List[int]]], optional*) – Similar to *recommendable_items*, but this time the recommendable items can vary among users. Defaults to None.
- **masked_interactions** (*Optional[Union[scipy.sparse.csr_matrix, scipy.sparse.csc_matrix]], optional*) – If set, this matrix masks the score output of recommender model where it is non-zero. If none, the mask will be the training matrix (`input_interaction`) it self.
- **n_threads** (*int, optional*) – Specifies the Number of threads to sort scores and compute the evaluation metrics. If `None`, the environment variable `"IRSPACK_NUM_THREADS_DEFAULT"` will be looked up, and if the variable is not set, it will be set to `os.cpu_count()`. Defaults to None.

- **recall_with_cutoff** (*bool, optional*) – This affects the definition of recall. If `True`, for each user, recall will be evaluated by

$$\frac{N_{\text{hit}}}{\min(\text{cutoff}, N_{\text{ground truth}})}$$

If `False`, this will be

$$\frac{N_{\text{hit}}}{N_{\text{ground truth}}}$$

- **mb_size** (*int, optional*) – The rows of chunked user score. Defaults to 1024.

__init__(*input_interaction*, *ground_truth*, *cutoff=10*, *target_metric='ndcg'*, *recommendable_items=None*, *per_user_recommendable_items=None*, *masked_interactions=None*, *n_threads=None*, *recall_with_cutoff=False*, *mb_size=1024*)

Parameters

- **input_interaction** (*Union[csr_matrix, csc_matrix]*) –
- **ground_truth** (*Union[csr_matrix, csc_matrix]*) –
- **cutoff** (*int*) –
- **target_metric** (*str*) –
- **recommendable_items** (*Optional[List[int]]*) –
- **per_user_recommendable_items** (*Union[None, List[List[int]], csr_matrix, csc_matrix]*) –
- **masked_interactions** (*Optional[Union[csr_matrix, csc_matrix]]*) –
- **n_threads** (*Optional[int]*) –
- **recall_with_cutoff** (*bool*) –
- **mb_size** (*int*) –

Methods

__init__(input_interaction, ground_truth[, ...])	
get_score(model)	Compute the score with the cutoff being `self.cutoff`.
get_scores(model, cutoffs)	Compute the score with the specified cutoffs.
get_target_score(model)	Compute the optimization target score (self.target_metric) with the cutoff being `self.cutoff`.

Attributes

`get_score`(*model*)

Compute the score with the cutoff being `self.cutoff`.

Parameters
model (BaseRecommender) – The evaluated recommender.

Returns
metric values.

Return type
Dict[str, float]

`get_scores`(*model*, *cutoffs*)

Compute the score with the specified cutoffs.

Parameters

- **model** (BaseRecommender) – The evaluated recommender.
- **cutoffs** (*List[int]*) – for each value in cutoff, the class computes the metric values.

Returns
The Resulting metric values. This time, the result will look like `{"ndcg@20": 0.35, "map@20": 0.2, ...}`.

Return type
Dict[str, float]

`get_target_score`(*model*)

Compute the optimization target score (self.target_metric) with the cutoff being `self.cutoff`.

Parameters
model (BaseRecommender) – The evaluated model.

Returns
The metric value.

Return type
float

1.4.2 Recommenders

BaseRecommender	The base class for all (hot) recommenders.
TopPopRecommender	A simple recommender system based on the popularity of the items in the training set (without any personalization).
IALSRecommender	Implementation of implicit Alternating Least Squares (iALS) or Weighted Matrix Factorization (WMF).
P3alphaRecommender	Recommendation with 3-steps random walk, proposed in
RP3betaRecommender	3-Path random walk with the item-popularity penalization:
TruncatedSVDRecommender	Use (randomized) SVD to factorize the input matrix into low-rank matrices.
CosineKNNRecommender	K-nearest neighbor recommender system based on cosine similarity.
AsymmetricCosineKNNRecommender	K-nearest neighbor recommender system based on asymmetric cosine similarity.
JaccardKNNRecommender	K-nearest neighbor recommender system based on Jaccard similarity.
TverskyIndexKNNRecommender	K-nearest neighbor recommender system based on Tversky Index.
CosineUserKNNRecommender	K-nearest neighbor recommender system based on cosine similarity.
AsymmetricCosineUserKNNRecommender	K-nearest neighbor recommender system based on asymmetric cosine similarity.
SLIMRecommender	SLIM with ElasticNet-type loss function:
DenseSLIMRecommender	Implementation of DenseSLIM or Embarrassingly Shallow AutoEncoder (EASE ^R).
get_recommender_class	Get recommender class from its class name.

irspack.recommenders.BaseRecommender

class irspack.recommenders.**BaseRecommender**(*X_train_all*, ***kwargs*)

Bases: `object`

The base class for all (hot) recommenders.

Parameters

- **X_train_all** (*csr_matrix|csc_matrix|np.ndarray*) – user/item interaction matrix. each row correspods to a user's interaction with items.
- **kwargs** (*Any*) –

__init__(*X_train_all*, ***kwargs*)

Parameters

- **X_train_all** (*Union[csr_matrix, csc_matrix]*) –
- **kwargs** (*Any*) –

Return type
None

Methods

__init__(X_train_all, **kwargs)	
default_suggest_parameter(trial, fixed_params)	
from_config(X_train_all, config)	
get_score(user_indices)	Compute the item recommendation score for a subset of users.
get_score_block(begin, end)	Compute the score for a block of the users.
get_score_cold_user(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_cold_user_remove_seen(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_remove_seen(user_indices)	Compute the item score and mask the item in the training set.
get_score_remove_seen_block(begin, end)	Compute the score for a block of the users, and mask the items in the training set.
learn()	Learns and returns itself.
learn_with_optimizer(evaluator, trial[, ...])	Learning procedures with early stopping and pruning.
tune(data, evaluator[, n_trials, timeout, ...])	Perform the optimization step.
tune_with_study(study, data, evaluator[, ...])	

Attributes

config_class	
default_tune_range	
X_train_all	The matrix to feed into recommender.

X_train_all: csr_matrix

The matrix to feed into recommender.

abstract get_score(*user_indices*)

Compute the item recommendation score for a subset of users.

Parameters
user_indices (*ndarray*) – The index defines the subset of users.

Returns
The item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

get_score_block(*begin*, *end*)

Compute the score for a block of the users.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

get_score_cold_user(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed item scores for users. Its shape is equal to X.

Return type
ndarray

get_score_cold_user_remove_seen(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix. The score will then be masked by the input.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed & masked item scores for users. Its shape is equal to X.

Return type
ndarray

get_score_remove_seen(*user_indices*)

Compute the item score and mask the item in the training set. Masked items will have the score -inf.

Parameters
user_indices (*ndarray*) – Specifies the subset of users.

Returns
The masked item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

get_score_remove_seen_block(*begin*, *end*)

Compute the score for a block of the users, and mask the items in the training set. Masked items will have the score -inf.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The masked item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`learn`()

Learns and returns itself.

Returns
The model after fitting process.

Parameters
self (*R*) –

Return type
R

`learn_with_optimizer`(*evaluator*, *trial*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*)

Learning procedures with early stopping and pruning.

Parameters

- **evaluator** (*Optional[evaluation.Evaluator]*) – The evaluator to measure the score.
- **trial** (*Optional[Trial]*) – The current optuna trial under the study (if any.)
- **max_epoch** (*int*) – Maximal number of epochs. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 128.
- **validate_epoch** (*int*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **validate_epoch** – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

Return type
None

`classmethod tune`(*data*, *evaluator*, *n_trials=20*, *timeout=None*, *data_suggest_function=None*, *parameter_suggest_function=None*, *fixed_params={}*, *random_seed=None*, *prunning_n_startup_trials=10*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*, *logger=None*)

Perform the optimization step. *optuna.Study* object is created inside this function.

Parameters

- **data** (*Optional[Union[csr_matrix, csc_matrix]]*) – The training data. You can also provide tunable parameter dependent training data by providing *data_suggest_function*. In that case, data must be *None*.
- **evaluator** (*evaluation.Evaluator*) – The validation evaluator that measures the performance of the recommenders.
- **n_trials** (*int*) – The number of expected trials (including pruned ones). Defaults to 20.
- **timeout** (*Optional[int]*) – If set to some value (in seconds), the study will exit after that time period. Note that the running trials is not interrupted, though. Defaults to *None*.
- **data_suggest_function** (*Optional[Callable[[Trial], Union[csr_matrix, csc_matrix]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns training data. Defaults to *None*.

- **parameter_suggest_function** (*Optional[Callable[[Trial], Dict[str, Any]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns *Dict[str, Any]* (i.e., some keyword arguments of the recommender class). If *None*, *cls.default_suggest_parameter* will be used for the parameter suggestion. Defaults to *None*.
- **fixed_params** (*Dict[str, Any]*) – Fixed parameters passed to recommenders during the optimization procedure. This will replace the suggested parameter (either by *cls.default_suggest_parameter* or *parameter_suggest_function*). Defaults to *dict()*.
- **random_seed** (*Optional[int]*) – The random seed to control *optuna.samplers.TPESampler*. Defaults to *None*.
- **prunning_n_startup_trials** (*int*) – *n_startup_trials* argument passed to the constructor of *optuna.pruners.MedianPruner*.
- **max_epoch** (*int*) – The maximal number of epochs for the training. If iterative learning procedure is not available, this parameter will be ignored.
- **validate_epoch** (*int, optional*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int, optional*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5. Defaults to 5.
- **logger** (*Optional[Logger]*) –

Returns

A tuple that consists of

1. A dict containing the best paramaters. This dict can be passed to the recommender as `**kwargs`.
2. A `pandas.DataFrame` that contains the history of optimization.

Return type
Tuple[*Dict*[str, *Any*], *DataFrame*]

irspack.recommenders.TopPopRecommender

class irspack.recommenders.**TopPopRecommender**(*X_train*)

Bases: *BaseRecommender*

A simple recommender system based on the popularity of the items in the training set (without any personalization).

Parameters

- **Union[scipy.sparse.csr_matrix** (*X_train*) – Input interaction matrix.
- **scipy.sparse.csc_matrix])** – Input interaction matrix.
- **X_train** (*Union[csr_matrix, csc_matrix]*) –

__init__(*X_train*)

Parameters
X_train (*Union[csr_matrix, csc_matrix]*) –

Methods

__init__(X_train)	
default_suggest_parameter(trial, fixed_params)	
from_config(X_train_all, config)	
get_score(user_indices)	Compute the item recommendation score for a subset of users.
get_score_block(begin, end)	Compute the score for a block of the users.
get_score_cold_user(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_cold_user_remove_seen(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_remove_seen(user_indices)	Compute the item score and mask the item in the training set.
get_score_remove_seen_block(begin, end)	Compute the score for a block of the users, and mask the items in the training set.
learn()	Learns and returns itself.
learn_with_optimizer(evaluator, trial[, ...])	Learning procedures with early stopping and pruning.
tune(data, evaluator[, n_trials, timeout, ...])	Perform the optimization step.
tune_with_study(study, data, evaluator[, ...])	

Attributes

default_tune_range
score
score_

X_train_all: sps.csr_matrix

The matrix to feed into recommender.

get_score(*user_indices*)

Compute the item recommendation score for a subset of users.

Parameters

user_indices (*ndarray*) – The index defines the subset of users.

Returns

The item scores. Its shape will be (len(user_indices), self.n_items)

Return type

ndarray

get_score_block(*begin*, *end*)

Compute the score for a block of the users.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`get_score_cold_user`(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_cold_user_remove_seen`(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix. The score will then be masked by the input.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed & masked item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_remove_seen`(*user_indices*)

Compute the item score and mask the item in the training set. Masked items will have the score -inf.

Parameters
user_indices (*ndarray*) – Specifies the subset of users.

Returns
The masked item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

`get_score_remove_seen_block`(*begin*, *end*)

Compute the score for a block of the users, and mask the items in the training set. Masked items will have the score -inf.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The masked item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`learn`()

Learns and returns itself.

Returns
The model after fitting process.

Parameters
self (*R*) –

Return type
R

`learn_with_optimizer`(*evaluator*, *trial*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*)

Learning procedures with early stopping and pruning.

Parameters

- **evaluator** (*Optional[evaluation.Evaluator]*) – The evaluator to measure the score.
- **trial** (*Optional[Trial]*) – The current optuna trial under the study (if any.)
- **max_epoch** (*int*) – Maximal number of epochs. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 128.
- **validate_epoch** (*int*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **validate_epoch** – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

Return type
None

`classmethod tune`(*data*, *evaluator*, *n_trials=20*, *timeout=None*, *data_suggest_function=None*, *parameter_suggest_function=None*, *fixed_params={}*, *random_seed=None*, *prunning_n_startup_trials=10*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*, *logger=None*)

Perform the optimization step. *optuna.Study* object is created inside this function.

Parameters

- **data** (*Optional[Union[csr_matrix, csc_matrix]]*) – The training data. You can also provide tunable parameter dependent training data by providing *data_suggest_function*. In that case, data must be *None*.
- **evaluator** (*evaluation.Evaluator*) – The validation evaluator that measures the performance of the recommenders.
- **n_trials** (*int*) – The number of expected trials (including pruned ones). Defaults to 20.
- **timeout** (*Optional[int]*) – If set to some value (in seconds), the study will exit after that time period. Note that the running trials is not interrupted, though. Defaults to *None*.
- **data_suggest_function** (*Optional[Callable[[Trial], Union[csr_matrix, csc_matrix]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns training data. Defaults to *None*.

- **parameter_suggest_function** (*Optional[Callable[[Trial], Dict[str, Any]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns *Dict[str, Any]* (i.e., some keyword arguments of the recommender class). If *None*, *cls.default_suggest_parameter* will be used for the parameter suggestion. Defaults to *None*.
- **fixed_params** (*Dict[str, Any]*) – Fixed parameters passed to recommenders during the optimization procedure. This will replace the suggested parameter (either by *cls.default_suggest_parameter* or *parameter_suggest_function*). Defaults to *dict()*.
- **random_seed** (*Optional[int]*) – The random seed to control *optuna.samplers.TPESampler*. Defaults to *None*.
- **prunning_n_startup_trials** (*int*) – *n_startup_trials* argument passed to the constructor of *optuna.pruners.MedianPruner*.
- **max_epoch** (*int*) – The maximal number of epochs for the training. If iterative learning procedure is not available, this parameter will be ignored.
- **validate_epoch** (*int, optional*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int, optional*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5. Defaults to 5.
- **logger** (*Optional[Logger]*) –

Returns

A tuple that consists of

1. A dict containing the best paramaters. This dict can be passed to the recommender as `**kwargs`.
2. A `pandas.DataFrame` that contains the history of optimization.

Return type
Tuple[*Dict*[str, *Any*], *DataFrame*]

irspack.recommenders.IALSRecommender

class irspack.recommenders.**IALSRecommender**(*X_train_all*, *n_components=20*, *alpha0=0.0*, *reg=0.001*, *nu=1.0*, *confidence_scaling='none'*, *epsilon=1.0*, *init_std=0.1*, *solver_type='CG'*, *max_cg_steps=3*, *ialspp_subspace_dimension=64*, *loss_type='IALSPP'*, *nu_star=None*, *random_seed=42*, *n_threads=None*, *train_epochs=16*, *prediction_time_max_cg_steps=5*, *prediction_time_ialspp_iteration=7*)

Bases: `BaseRecommenderWithEarlyStopping`, `BaseRecommenderWithUserEmbedding`, `BaseRecommenderWithItemEmbedding`

Implementation of implicit Alternating Least Squares (iALS) or Weighted Matrix Factorization (WMF).

By default, it tries to minimize the following loss:

$$\frac{1}{2}\sum_{u,i\in S} c_{ui}(\mathbf{u}_u\cdot\mathbf{v}_i-1)^2+\frac{\alpha_0}{2}\sum_{u,i}(\mathbf{u}_u\cdot\mathbf{v}_i)^2+\frac{\mathrm{reg}}{2}\left(\sum_u(\alpha_0 I+N_u)^\nu||\mathbf{u}_u||^2+\sum_i(\alpha_0 U+N_i)^\nu||\mathbf{v}_i||^2\right)$$

where S denotes the set of all pairs wher X_{ui} is non-zero.

See the seminal paper:

- Collaborative filtering for implicit feedback datasets

By default it uses a conjugate gradient descent version:

- Applications of the conjugate gradient method for implicit feedback collaborative filtering

The loss above is slightly different from the original version. See the following paper for the loss used here

- Revisiting the Performance of iALS on Item Recommendation Benchmarks

Parameters

- **X_train_all** (*Union[scipy.sparse.csr_matrix, scipy.sparse.csc_matrix]*) – Input interaction matrix.
- **n_components** (*int, optional*) – The dimension for latent factor. Defaults to 20.
- **alpha0** (*float, optional*) – The "unobserved" weight.
- **reg** (*float, optional*) – Regularization coefficient for both user & item factors. Defaults to 1e-3.
- **nu** (*float, optional*) – Controlles frequency regularization introduced in the paper, "Revisiting the Performance of iALS on Item Recommendation Benchmarks".
- **confidence_scaling** (*str, optional*) – Specifies how to scale confidence scaling c_{ui}. Must be either "none" or "log". If "none", the non-zero (not-necessarily 1) X_{ui} yields

  $$c_{ui} = A + X_{ui}$$

  If "log",

  $$c_{ui} = A + \log(1 + X_{ui}/\epsilon)$$

  The constant A above will be 0 if `loss_type` is `"IALSPP"`, α_0 if `loss_type` is `"ORIGINAL"`.

  Defaults to "none".
- **epsilon** (*float, optional*) – The ϵ parameter for log-scaling described above. Will not have any effect if *confidence_scaling* is "none". Defaults to 1.0f.
- **init_std** (*float, optional*) – Standard deviation for initialization normal distribution. The actual std for each user/item vector components are scaled by *1 / n_components ** .5*. Defaults to 0.1.
- **solver_type** (*"CHOLESKY" | "CG" | "IALSPP", optional*) – Which solver to use. Defaults to "CG".
- **max_cg_steps** (*int, optional*) – Maximal number of conjute gradient descent steps during the training time. Defaults to 3. Used only when `solver_type=="CG"`. By increasing this parameter, the result will be closer to Cholesky decomposition method (i.e., when `solver_type == "CHOLESKY"`), but it wll take longer time.
- **ialspp_subspace_dimension** (*int, optional*) – The subspace dimension of iALS++ (ignored if the `solver_type` is not "IALSPP"). If this value is 1, specialized implementation described in Fast Matrix Factorization for Online Recommendation with Implicit Feedback will be used instead. Defaults to 64.

- **loss_type** (*Literal["IALSPP", "ORIGINAL"], optional*) – Specifies the subtle difference between iALS++ vs Original Loss.
- **nu_star** (*Optional[float], optional*) – If not *None*, used as the reference scale for nu described in the "Revisiting…" paper. Defaults to None.
- **random_seed** (*int, optional*) – The random seed to initialize the parameters.
- **n_threads** (*Optional[int], optional*) – Specifies the number of threads to use for the computation. If `None`, the environment variable `"IRSPACK_NUM_THREADS_DEFAULT"` will be looked up, and if the variable is not set, it will be set to `os.cpu_count()`. Defaults to None.
- **train_epochs** (*int, optional*) – Maximal number of epochs. Defaults to 16.
- **prediction_time_max_cg_steps** (*int, optional*) – Maximal number of conjute gradient descent steps during the prediction time, i.e., the case when a user unseen at the training time is given as a history matrix. Defaults to 5.
- **prediction_time_ialspp_iteration** (*int*) –

Examples

```
>>> from irspack import IALSRecommender, rowwise_train_test_split, Evaluator
>>> from irspack.utils.sample_data import mf_example_data
>>> X = mf_example_data(100, 30, random_state=1)
>>> X_train, X_test = rowwise_train_test_split(X, random_state=0)
>>> rec = IALSRecommender(X_train)
>>> rec.learn()
>>> evaluator=Evaluator(X_test)
>>> print(evaluator.get_scores(rec, [20]))
OrderedDict([('hit@20', 1.0), ('recall@20', 0.9003412698412698), ('ndcg@20', 0.
↪6175493479217139), ('map@20', 0.3848785870622406), ('precision@20', 0.3385), (
↪'gini_index@20', 0.0814), ('entropy@20', 3.382497875272383), ('appeared_item@20',␣
↪30.0)])
```

__init__(*X_train_all*, *n_components=20*, *alpha0=0.0*, *reg=0.001*, *nu=1.0*, *confidence_scaling='none'*, *epsilon=1.0*, *init_std=0.1*, *solver_type='CG'*, *max_cg_steps=3*, *ialspp_subspace_dimension=64*, *loss_type='IALSPP'*, *nu_star=None*, *random_seed=42*, *n_threads=None*, *train_epochs=16*, *prediction_time_max_cg_steps=5*, *prediction_time_ialspp_iteration=7*)

Parameters

- **X_train_all** (*Union[csr_matrix, csc_matrix]*) –
- **n_components** (*int*) –
- **alpha0** (*float*) –
- **reg** (*float*) –
- **nu** (*float*) –
- **confidence_scaling** (*str*) –
- **epsilon** (*float*) –
- **init_std** (*float*) –
- **solver_type** (*typing_extensions.Literal[CG, CHOLESKY, IALSPP]*) –

- **max_cg_steps** (*int*) –
- **ialspp_subspace_dimension** (*int*) –
- **loss_type** (*typing_extensions.Literal[IALSPP, ORIGINAL]*) –
- **nu_star** (*Optional[float]*) –
- **random_seed** (*int*) –
- **n_threads** (*Optional[int]*) –
- **train_epochs** (*int*) –
- **prediction_time_max_cg_steps** (*int*) –
- **prediction_time_ialspp_iteration** (*int*) –

Return type
None

Methods

__init__(X_train_all[, n_components, ...])	
compute_item_embedding(X)	Given an unknown items' interaction with known user, computes the latent factors of the items by least square (fixing user embeddings).
compute_user_embedding(X)	Given an unknown users' interaction with known items, computes the latent factors of the users by least square (fixing item embeddings).
default_suggest_parameter(trial, fixed_params)	
from_config(X_train_all, config)	
get_item_embedding()	Get item embedding vectors.
get_score(user_indices)	Compute the item recommendation score for a subset of users.
get_score_block(begin, end)	Compute the score for a block of the users.
get_score_cold_user(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_cold_user_remove_seen(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_from_item_embedding(user_indices, ...)	
get_score_from_user_embedding(user_embedding)	Compute the item score from user embedding.
get_score_remove_seen(user_indices)	Compute the item score and mask the item in the training set.
get_score_remove_seen_block(begin, end)	Compute the score for a block of the users, and mask the items in the training set.
get_user_embedding()	Get user embedding vectors.
learn()	Learns and returns itself.
learn_with_optimizer(evaluator, trial[, ...])	Learning procedures with early stopping and pruning.
load_state()	
run_epoch()	
save_state()	
start_learning()	
tune(data, evaluator[, n_trials, timeout, ...])	Perform the optimization step.
tune_doubling_dimension(data, evaluator, ...)	Perform tuning gradually doubling *n_components*.
tune_with_study(study, data, evaluator[, ...])	

Attributes

default_tune_range

trainer_as_ials

X_train_all: sps.csr_matrix

The matrix to feed into recommender.

compute_item_embedding(*X*)

Given an unknown items' interaction with known user, computes the latent factors of the items by least square (fixing user embeddings).

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The interaction history of the new users. `X.shape[0]` must be equal to `self.n_users`.

Return type
ndarray

compute_user_embedding(*X*)

Given an unknown users' interaction with known items, computes the latent factors of the users by least square (fixing item embeddings).

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The interaction history of the new users. `X.shape[1]` must be equal to `self.n_items`.

Return type
ndarray

get_item_embedding()

Get item embedding vectors.

Returns
The latent vector representation of items. Its number of rows is equal to the number of the items.

Return type
ndarray

get_score(*user_indices*)

Compute the item recommendation score for a subset of users.

Parameters
user_indices (*ndarray*) – The index defines the subset of users.

Returns
The item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

get_score_block(*begin*, *end*)

Compute the score for a block of the users.

Parameters

- **begin** (*int*) – where the evaluated user block begins.

- **end** (*int*) – where the evaluated user block ends.

Returns
The item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`get_score_cold_user`(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_cold_user_remove_seen`(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix. The score will then be masked by the input.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed & masked item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_from_user_embedding`(*user_embedding*)

Compute the item score from user embedding. Mainly used for cold-start scenario.

Parameters
user_embedding (*ndarray*) – Latent user representation obtained elsewhere.

Returns
The score array. Its shape will be `(user_embedding.shape[0], self.n_items)`

Return type
DenseScoreArray

`get_score_remove_seen`(*user_indices*)

Compute the item score and mask the item in the training set. Masked items will have the score -inf.

Parameters
user_indices (*ndarray*) – Specifies the subset of users.

Returns
The masked item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

`get_score_remove_seen_block`(*begin*, *end*)

Compute the score for a block of the users, and mask the items in the training set. Masked items will have the score -inf.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The masked item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`get_user_embedding`()

Get user embedding vectors.

Returns
The latent vector representation of users. Its number of rows is equal to the number of the users.

Return type
ndarray

`learn`()

Learns and returns itself.

Returns
The model after fitting process.

Parameters
self (*R*) –

Return type
R

`learn_with_optimizer`(*evaluator*, *trial*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*)

Learning procedures with early stopping and pruning.

Parameters

- **evaluator** (*Optional[evaluation.Evaluator]*) – The evaluator to measure the score.
- **trial** (*Optional[Trial]*) – The current optuna trial under the study (if any.)
- **max_epoch** (*int*) – Maximal number of epochs. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 128.
- **validate_epoch** (*int*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **validate_epoch** – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

Return type
None

classmethod **tune**(*data*, *evaluator*, *n_trials=20*, *timeout=None*, *data_suggest_function=None*, *parameter_suggest_function=None*, *fixed_params={}*, *random_seed=None*, *prunning_n_startup_trials=10*, *max_epoch=16*, *validate_epoch=1*, *score_degradation_max=3*, *logger=None*)

Perform the optimization step. *optuna.Study* object is created inside this function.

Parameters

- **data** (*Optional[Union[csr_matrix, csc_matrix]]*) – The training data. You can also provide tunable parameter dependent training data by providing *data_suggest_function*. In that case, data must be *None*.
- **evaluator** (evaluation.Evaluator) – The validation evaluator that measures the performance of the recommenders.
- **n_trials** (*int*) – The number of expected trials (including pruned ones). Defaults to 20.
- **timeout** (*Optional[int]*) – If set to some value (in seconds), the study will exit after that time period. Note that the running trials is not interrupted, though. Defaults to *None*.
- **data_suggest_function** (*Optional[Callable[[Trial], Union[csr_matrix, csc_matrix]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns training data. Defaults to *None*.
- **parameter_suggest_function** (*Optional[Callable[[Trial], Dict[str, Any]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns *Dict[str, Any]* (i.e., some keyword arguments of the recommender class). If *None*, *cls.default_suggest_parameter* will be used for the parameter suggestion. Defaults to *None*.
- **fixed_params** (*Dict[str, Any]*) – Fixed parameters passed to recommenders during the optimization procedure. This will replace the suggested parameter (either by *cls.default_suggest_parameter* or *parameter_suggest_function*). Defaults to *dict()*.
- **random_seed** (*Optional[int]*) – The random seed to control *optuna.samplers.TPESampler*. Defaults to *None*.
- **prunning_n_startup_trials** (*int*) – *n_startup_trials* argument passed to the constructor of *optuna.pruners.MedianPruner*.
- **max_epoch** (*int*) – The maximal number of epochs for the training. If iterative learning procedure is not available, this parameter will be ignored.
- **validate_epoch** (*int, optional*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int, optional*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5. Defaults to 5.
- **logger** (*Optional[Logger]*) –

Returns

A tuple that consists of

1. A dict containing the best paramaters. This dict can be passed to the recommender as `**kwargs`.
2. A `pandas.DataFrame` that contains the history of optimization.

Return type
Tuple[*Dict*[str, *Any*], *DataFrame*]

classmethod tune_doubling_dimension(*data*, *evaluator*, *initial_dimension*, *maximal_dimension*, *storage=None*, *study_name_prefix=None*, *n_trials_initial=40*, *n_trials_following=20*, *n_startup_trials_initial=10*, *n_startup_trials_following=5*, *max_epoch=16*, *validate_epoch=1*, *score_degradation_max=3*, *neighborhood_scale=3.0*, *suggest_function_initial=None*, *random_seed=None*)

Perform tuning gradually doubling *n_components*. Typically, with the initial *n_components*, the search will be more exhaustive, and with larger *n_components*, less exploration will be done around previously found parameters. This strategy is described in Revisiting the Performance of iALS on Item Recommendation Benchmarks.

Parameters

- **initial_dimension** (*int*) – The initial dimension.
- **maximal_dimension** (*int*) – The maximal (inclusive) dimension to be tried.
- **storage** (*Optional[RDBStorage]*) – The storage where multiple *optuna.Study* will be created corresponding to the various dimensions. If *None*, all *Study* will be created in-memory.
- **study_name_prefix** (*Optional[str]*) – The prefix for the names of *optuna.Study*. For dimension *d*, the full name of the *Study* will be *"{study_name_prefix}_{d}"*. If *None*, we will use a random string for this prefix.
- **n_trials_initial** (*int*) – The number of trials for the initial dimension.
- **n_trials_following** (*int*) – The number of trials for the following dimensions.
- **n_startup_trials_initial** (*int*) – Passed on to *n_startup_trials* argument of *optuna.pruners.MedianPruner* in the initial *optuna.Study*. Defaults to *10*.
- **n_startup_trials_following** (*int*) – Passed on to *n_startup_trials* argument of *optuna.pruners.MedianPruner* in the following *optuna.Study*. Defaults to *5*.
- **neighborhood_scale** (*float*) – *alpha_0* and *reg* parameters will be searched within the log-uniform range [*previous_dimension_result / neighborhood_scale*, *previous_dimension_result * neighborhood_scale*]. Defaults to *3.0*
- **suggest_overwrite_initial** – Overwrites the suggestion parameters in the initial *optuna.Study*. Defaults to *[]*.
- **random_seed** (*Optional[int]*) – The random seed to control `optuna.samplers.TPESampler`. Defaults to *None*.
- **data** (*Union[csr_matrix, csc_matrix]*) –
- **evaluator** (Evaluator) –
- **max_epoch** (*int*) –
- **validate_epoch** (*int*) –
- **score_degradation_max** (*int*) –
- **suggest_function_initial** (*Optional[Callable[[Trial], Dict[str, Any]]]*) –

Returns

A tuple that consists of

1. A dict containing the best paramaters. This dict can be passed to the recommender as `**kwargs`.
2. A `pandas.DataFrame` that contains the history of optimization for all dimensions.

Return type
Tuple[*Dict*[str, *Any*], *DataFrame*]

irspack.recommenders.P3alphaRecommender

`class irspack.recommenders.P3alphaRecommender(X_train_all, alpha=1, top_k=None, normalize_weight=False, n_threads=None)`

Bases: `BaseSimilarityRecommender`

Recommendation with 3-steps random walk, proposed in

- Random Walks in Recommender Systems: Exact Computation and Simulations

The version here implements its view as KNN-based method, as pointed out in

- A Troubling Analysis of Reproducibility and Progress in Recommender Systems Research

Parameters

- **X_train_all** (*Union[scipy.sparse.csr_matrix, scipy.sparse.csc_matrix]*) – Input interaction matrix.
- **alpha** (*float, optional*) – The power to which `X_train_all` is exponentiated. Defaults to 1. Note that this has no effect if all the entries in `X_train_all` are equal.
- **top_k** (*Optional[int], optional*) – Maximal number of non-zero entries retained for each column of the similarity matrix `W`.
- **normalize_weight** (*bool, optional*) – Whether to perform row-wise normalization of `W`. Defaults to False.
- **n_threads** (*Optional[int], optional*) – Specifies the number of threads to use for the computation. If `None`, the environment variable `"IRSPACK_NUM_THREADS_DEFAULT"` will be looked up, and if the variable is not set, it will be set to `os.cpu_count()`. Defaults to None.

`__init__(X_train_all, alpha=1, top_k=None, normalize_weight=False, n_threads=None)`

Parameters

- **X_train_all** (*Union[csr_matrix, csc_matrix]*) –
- **alpha** (*float*) –
- **top_k** (*Optional[int]*) –
- **normalize_weight** (*bool*) –
- **n_threads** (*Optional[int]*) –

Methods

__init__(X_train_all[, alpha, top_k, ...])	
default_suggest_parameter(trial, fixed_params)	
from_config(X_train_all, config)	
get_score(user_indices)	Compute the item recommendation score for a subset of users.
get_score_block(begin, end)	Compute the score for a block of the users.
get_score_cold_user(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_cold_user_remove_seen(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_remove_seen(user_indices)	Compute the item score and mask the item in the training set.
get_score_remove_seen_block(begin, end)	Compute the score for a block of the users, and mask the items in the training set.
learn()	Learns and returns itself.
learn_with_optimizer(evaluator, trial[, ...])	Learning procedures with early stopping and pruning.
tune(data, evaluator[, n_trials, timeout, ...])	Perform the optimization step.
tune_with_study(study, data, evaluator[, ...])	

Attributes

W	The computed item-item similarity weight matrix.
default_tune_range	

property W: Union[csr_matrix, csc_matrix, ndarray]

The computed item-item similarity weight matrix.

X_train_all: sps.csr_matrix

The matrix to feed into recommender.

get_score(*user_indices*)

Compute the item recommendation score for a subset of users.

Parameters
user_indices (*ndarray*) – The index defines the subset of users.

Returns
The item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

get_score_block(*begin*, *end*)

Compute the score for a block of the users.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`get_score_cold_user`(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_cold_user_remove_seen`(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix. The score will then be masked by the input.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed & masked item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_remove_seen`(*user_indices*)

Compute the item score and mask the item in the training set. Masked items will have the score -inf.

Parameters
user_indices (*ndarray*) – Specifies the subset of users.

Returns
The masked item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

`get_score_remove_seen_block`(*begin*, *end*)

Compute the score for a block of the users, and mask the items in the training set. Masked items will have the score -inf.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The masked item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`learn`()

Learns and returns itself.

Returns
The model after fitting process.

Parameters
self (*R*) –

Return type
R

`learn_with_optimizer`(*evaluator*, *trial*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*)

Learning procedures with early stopping and pruning.

Parameters

- **evaluator** (*Optional[evaluation.Evaluator]*) – The evaluator to measure the score.
- **trial** (*Optional[Trial]*) – The current optuna trial under the study (if any.)
- **max_epoch** (*int*) – Maximal number of epochs. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 128.
- **validate_epoch** (*int*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **validate_epoch** – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

Return type
None

`classmethod tune`(*data*, *evaluator*, *n_trials=20*, *timeout=None*, *data_suggest_function=None*, *parameter_suggest_function=None*, *fixed_params={}*, *random_seed=None*, *prunning_n_startup_trials=10*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*, *logger=None*)

Perform the optimization step. *optuna.Study* object is created inside this function.

Parameters

- **data** (*Optional[Union[csr_matrix, csc_matrix]]*) – The training data. You can also provide tunable parameter dependent training data by providing *data_suggest_function*. In that case, data must be *None*.
- **evaluator** (*evaluation.Evaluator*) – The validation evaluator that measures the performance of the recommenders.
- **n_trials** (*int*) – The number of expected trials (including pruned ones). Defaults to 20.
- **timeout** (*Optional[int]*) – If set to some value (in seconds), the study will exit after that time period. Note that the running trials is not interrupted, though. Defaults to *None*.
- **data_suggest_function** (*Optional[Callable[[Trial], Union[csr_matrix, csc_matrix]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns training data. Defaults to *None*.

- **parameter_suggest_function** (*Optional[Callable[[Trial], Dict[str, Any]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns *Dict[str, Any]* (i.e., some keyword arguments of the recommender class). If *None*, *cls.default_suggest_parameter* will be used for the parameter suggestion. Defaults to *None*.
- **fixed_params** (*Dict[str, Any]*) – Fixed parameters passed to recommenders during the optimization procedure. This will replace the suggested parameter (either by *cls.default_suggest_parameter* or *parameter_suggest_function*). Defaults to *dict()*.
- **random_seed** (*Optional[int]*) – The random seed to control *optuna.samplers.TPESampler*. Defaults to *None*.
- **prunning_n_startup_trials** (*int*) – *n_startup_trials* argument passed to the constructor of *optuna.pruners.MedianPruner*.
- **max_epoch** (*int*) – The maximal number of epochs for the training. If iterative learning procedure is not available, this parameter will be ignored.
- **validate_epoch** (*int, optional*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int, optional*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5. Defaults to 5.
- **logger** (*Optional[Logger]*) –

Returns

A tuple that consists of

1. A dict containing the best paramaters. This dict can be passed to the recommender as `**kwargs`.
2. A `pandas.DataFrame` that contains the history of optimization.

Return type
Tuple[*Dict*[str, *Any*], *DataFrame*]

irspack.recommenders.RP3betaRecommender

class irspack.recommenders.**RP3betaRecommender**(*X_train_all*, *alpha=1*, *beta=0.6*, *top_k=None*, *normalize_weight=False*, *n_threads=None*)

Bases: `BaseSimilarityRecommender`

3-Path random walk with the item-popularity penalization:

- Updatable, Accurate, Diverse, and Scalable Recommendations for Interactive Applications

The version here implements its view as KNN-based method, as pointed out in

- A Troubling Analysis of Reproducibility and Progress in Recommender Systems Research

Parameters

- **X_train_all** (*Union[scipy.sparse.csr_matrix, scipy.sparse.csc_matrix]*) – Input interaction matrix.
- **alpha** (*float, optional*) – The power to which `X_train_all` is exponentiated. Defaults to 1. Note that this has no effect if all the entries in `X_train_all` are equal.

- **beta** (*float, optional*) – Specifies how the user->item transition probability will be penalized by the popularity. Defaults to 0.6.
- **top_k** (*Optional[int], optional*) – Maximal number of non-zero entries retained
- **W.** (*for each column of the similarity matrix*) –
- **normalize_weight** (*bool, optional*) – Whether to perform row-wise normalization of `W`. Defaults to False.
- **n_threads** (*Optional[int], optional*) – Specifies the number of threads to use for the computation. If `None`, the environment variable `"IRSPACK_NUM_THREADS_DEFAULT"` will be looked up, and if the variable is not set, it will be set to `os.cpu_count()`. Defaults to None.

__init__(*X_train_all*, *alpha=1*, *beta=0.6*, *top_k=None*, *normalize_weight=False*, *n_threads=None*)

Parameters

- **X_train_all** (*Union[csr_matrix, csc_matrix]*) –
- **alpha** (*float*) –
- **beta** (*float*) –
- **top_k** (*Optional[int]*) –
- **normalize_weight** (*bool*) –
- **n_threads** (*Optional[int]*) –

Methods

__init__(X_train_all[, alpha, beta, top_k, ...])	
default_suggest_parameter(trial, fixed_params)	
from_config(X_train_all, config)	
get_score(user_indices)	Compute the item recommendation score for a subset of users.
get_score_block(begin, end)	Compute the score for a block of the users.
get_score_cold_user(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_cold_user_remove_seen(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_remove_seen(user_indices)	Compute the item score and mask the item in the training set.
get_score_remove_seen_block(begin, end)	Compute the score for a block of the users, and mask the items in the training set.
learn()	Learns and returns itself.
learn_with_optimizer(evaluator, trial[, ...])	Learning procedures with early stopping and pruning.
tune(data, evaluator[, n_trials, timeout, ...])	Perform the optimization step.
tune_with_study(study, data, evaluator[, ...])	

Attributes

W	The computed item-item similarity weight matrix.
default_tune_range	

property W: Union[csr_matrix, csc_matrix, ndarray]

The computed item-item similarity weight matrix.

X_train_all: sps.csr_matrix

The matrix to feed into recommender.

get_score(*user_indices*)

Compute the item recommendation score for a subset of users.

Parameters
user_indices (*ndarray*) – The index defines the subset of users.

Returns
The item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

get_score_block(*begin*, *end*)

Compute the score for a block of the users.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

get_score_cold_user(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed item scores for users. Its shape is equal to X.

Return type
ndarray

get_score_cold_user_remove_seen(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix. The score will then be masked by the input.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed & masked item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_remove_seen`(*user_indices*)

Compute the item score and mask the item in the training set. Masked items will have the score -inf.

Parameters
user_indices (*ndarray*) – Specifies the subset of users.

Returns
The masked item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

`get_score_remove_seen_block`(*begin*, *end*)

Compute the score for a block of the users, and mask the items in the training set. Masked items will have the score -inf.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The masked item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`learn`()

Learns and returns itself.

Returns
The model after fitting process.

Parameters
self (*R*) –

Return type
R

`learn_with_optimizer`(*evaluator*, *trial*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*)

Learning procedures with early stopping and pruning.

Parameters

- **evaluator** (*Optional[evaluation.Evaluator]*) – The evaluator to measure the score.
- **trial** (*Optional[Trial]*) – The current optuna trial under the study (if any.)
- **max_epoch** (*int*) – Maximal number of epochs. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 128.
- **validate_epoch** (*int*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **validate_epoch** – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

- **score_degradation_max** (*int*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

Return type
None

classmethod tune(*data*, *evaluator*, *n_trials=20*, *timeout=None*, *data_suggest_function=None*, *parameter_suggest_function=None*, *fixed_params={}*, *random_seed=None*, *prunning_n_startup_trials=10*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*, *logger=None*)

Perform the optimization step. *optuna.Study* object is created inside this function.

Parameters

- **data** (*Optional[Union[csr_matrix, csc_matrix]]*) – The training data. You can also provide tunable parameter dependent training data by providing *data_suggest_function*. In that case, data must be *None*.
- **evaluator** (evaluation.Evaluator) – The validation evaluator that measures the performance of the recommenders.
- **n_trials** (*int*) – The number of expected trials (including pruned ones). Defaults to 20.
- **timeout** (*Optional[int]*) – If set to some value (in seconds), the study will exit after that time period. Note that the running trials is not interrupted, though. Defaults to *None*.
- **data_suggest_function** (*Optional[Callable[[Trial], Union[csr_matrix, csc_matrix]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns training data. Defaults to *None*.
- **parameter_suggest_function** (*Optional[Callable[[Trial], Dict[str, Any]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns *Dict[str, Any]* (i.e., some keyword arguments of the recommender class). If *None*, *cls.default_suggest_parameter* will be used for the parameter suggestion. Defaults to *None*.
- **fixed_params** (*Dict[str, Any]*) – Fixed parameters passed to recommenders during the optimization procedure. This will replace the suggested parameter (either by *cls.default_suggest_parameter* or *parameter_suggest_function*). Defaults to *dict()*.
- **random_seed** (*Optional[int]*) – The random seed to control *optuna.samplers.TPESampler*. Defaults to *None*.
- **prunning_n_startup_trials** (*int*) – *n_startup_trials* argument passed to the constructor of *optuna.pruners.MedianPruner*.
- **max_epoch** (*int*) – The maximal number of epochs for the training. If iterative learning procedure is not available, this parameter will be ignored.
- **validate_epoch** (*int, optional*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int, optional*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5. Defaults to 5.
- **logger** (*Optional[Logger]*) –

Returns

A tuple that consists of

1. A dict containing the best paramaters. This dict can be passed to the recommender as `**kwargs`.
2. A `pandas.DataFrame` that contains the history of optimization.

Return type
Tuple[*Dict*[str, *Any*], *DataFrame*]

irspack.recommenders.TruncatedSVDRecommender

class irspack.recommenders.**TruncatedSVDRecommender**(*X_train_all*, *n_components=4*, *random_seed=0*)

Bases: *BaseRecommender*, BaseRecommenderWithUserEmbedding, BaseRecommenderWithItemEmbedding

Use (randomized) SVD to factorize the input matrix into low-rank matrices.

Parameters

- **X_train_all** (*csr_matrix*) – Input interaction matrix.
- **n_components** (*int*) – The rank of approximation. Defaults to 4. If this is larger than X_train_all, the value will be truncated into `X_train_all.shape[1]`
- **random_seed** (*int*) – The random seed to be passed on core TruncSVD.

__init__(*X_train_all*, *n_components=4*, *random_seed=0*)

Parameters

- **X_train_all** (*Union[csr_matrix, csc_matrix]*) –
- **n_components** (*int*) –
- **random_seed** (*int*) –

Return type
None

Methods

__init__(X_train_all[, n_components, ...])	
default_suggest_parameter(trial, fixed_params)	
from_config(X_train_all, config)	
get_item_embedding()	Get item embedding vectors.
get_score(user_indices)	Compute the item recommendation score for a subset of users.
get_score_block(begin, end)	Compute the score for a block of the users.
get_score_cold_user(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_cold_user_remove_seen(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_from_item_embedding(user_indices, ...)	
get_score_from_user_embedding(user_embedding)	Compute the item score from user embedding.
get_score_remove_seen(user_indices)	Compute the item score and mask the item in the training set.
get_score_remove_seen_block(begin, end)	Compute the score for a block of the users, and mask the items in the training set.
get_user_embedding()	Get user embedding vectors.
learn()	Learns and returns itself.
learn_with_optimizer(evaluator, trial[, ...])	Learning procedures with early stopping and pruning.
tune(data, evaluator[, n_trials, timeout, ...])	Perform the optimization step.
tune_with_study(study, data, evaluator[, ...])	

Attributes

decomposer
default_tune_range
z

X_train_all: csr_matrix

The matrix to feed into recommender.

get_item_embedding()

Get item embedding vectors.

Returns

The latent vector representation of items. Its number of rows is equal to the number of the items.

Return type
ndarray

`get_score`(*user_indices*)

Compute the item recommendation score for a subset of users.

Parameters
user_indices (*ndarray*) – The index defines the subset of users.

Returns
The item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

`get_score_block`(*begin*, *end*)

Compute the score for a block of the users.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`get_score_cold_user`(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_cold_user_remove_seen`(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix. The score will then be masked by the input.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed & masked item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_from_user_embedding`(*user_embedding*)

Compute the item score from user embedding. Mainly used for cold-start scenario.

Parameters
user_embedding (*ndarray*) – Latent user representation obtained elsewhere.

Returns
The score array. Its shape will be `(user_embedding.shape[0], self.n_items)`

Return type
DenseScoreArray

`get_score_remove_seen`(*user_indices*)

Compute the item score and mask the item in the training set. Masked items will have the score -inf.

Parameters
user_indices (*ndarray*) – Specifies the subset of users.

Returns
The masked item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

`get_score_remove_seen_block`(*begin*, *end*)

Compute the score for a block of the users, and mask the items in the training set. Masked items will have the score -inf.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The masked item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`get_user_embedding`()

Get user embedding vectors.

Returns
The latent vector representation of users. Its number of rows is equal to the number of the users.

Return type
ndarray

`learn`()

Learns and returns itself.

Returns
The model after fitting process.

Parameters
self (*R*) –

Return type
R

`learn_with_optimizer`(*evaluator*, *trial*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*)

Learning procedures with early stopping and pruning.

Parameters

- **evaluator** (*Optional[evaluation.Evaluator]*) – The evaluator to measure the score.

- **trial** (*Optional[Trial]*) – The current optuna trial under the study (if any.)
- **max_epoch** (*int*) – Maximal number of epochs. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 128.
- **validate_epoch** (*int*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **validate_epoch** – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

Return type
None

classmethod tune(*data*, *evaluator*, *n_trials=20*, *timeout=None*, *data_suggest_function=None*, *parameter_suggest_function=None*, *fixed_params={}*, *random_seed=None*, *prunning_n_startup_trials=10*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*, *logger=None*)

Perform the optimization step. *optuna.Study* object is created inside this function.

Parameters

- **data** (*Optional[Union[csr_matrix, csc_matrix]]*) – The training data. You can also provide tunable parameter dependent training data by providing *data_suggest_function*. In that case, data must be *None*.
- **evaluator** (evaluation.Evaluator) – The validation evaluator that measures the performance of the recommenders.
- **n_trials** (*int*) – The number of expected trials (including pruned ones). Defaults to 20.
- **timeout** (*Optional[int]*) – If set to some value (in seconds), the study will exit after that time period. Note that the running trials is not interrupted, though. Defaults to *None*.
- **data_suggest_function** (*Optional[Callable[[Trial], Union[csr_matrix, csc_matrix]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns training data. Defaults to *None*.
- **parameter_suggest_function** (*Optional[Callable[[Trial], Dict[str, Any]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns *Dict[str, Any]* (i.e., some keyword arguments of the recommender class). If *None*, *cls.default_suggest_parameter* will be used for the parameter suggestion. Defaults to *None*.
- **fixed_params** (*Dict[str, Any]*) – Fixed parameters passed to recommenders during the optimization procedure. This will replace the suggested parameter (either by *cls.default_suggest_parameter* or *parameter_suggest_function*). Defaults to *dict()*.
- **random_seed** (*Optional[int]*) – The random seed to control *optuna.samplers.TPESampler*. Defaults to *None*.
- **prunning_n_startup_trials** (*int*) – *n_startup_trials* argument passed to the constructor of *optuna.pruners.MedianPruner*.
- **max_epoch** (*int*) – The maximal number of epochs for the training. If iterative learning procedure is not available, this parameter will be ignored.
- **validate_epoch** (*int, optional*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

- **score_degradation_max** (*int, optional*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5. Defaults to 5.
- **logger** (*Optional[Logger]*) –

Returns

A tuple that consists of

1. A dict containing the best paramaters. This dict can be passed to the recommender as `**kwargs`.
2. A `pandas.DataFrame` that contains the history of optimization.

Return type
Tuple[*Dict*[str, *Any*], *DataFrame*]

irspack.recommenders.CosineKNNRecommender

class irspack.recommenders.**CosineKNNRecommender**(*X_train_all*, *shrinkage=0.0*, *normalize=False*, *top_k=100*, *feature_weighting='NONE'*, *bm25_k1=1.2*, *bm25_b=0.75*, *n_threads=None*)

Bases: `BaseKNNRecommender`

K-nearest neighbor recommender system based on cosine similarity. That is, the similarity matrix `W` is given by (column-wise top-k restricted)

$$\mathrm{W}_{i,j} = \begin{cases} \frac{\sum_u X_{ui}X_{uj}}{||X_{*i}||_2||X_{*j}||_2+\mathrm{shrinkage}} & \text{(if normalize = True)} \\ \sum_u X_{ui}X_{uj} & \text{(if normalize = False)} \end{cases}$$

Parameters

- **X_train_all** (*Union[scipy.sparse.csr_matrix, scipy.sparse.csc_matrix]*) – Input interaction matrix.
- **shrinkage** (*float, optional*) – The shrinkage parameter for regularization. Defaults to 0.0.
- **normalize** (*bool, optional*) – Whether to normalize the similarity. Defaults to False.
- **top_k** (*int, optional*) – Specifies the maximal number of allowed neighbors. Defaults to 100.
- **feature_weighting** (*str, optional*) – Specifies how to weight the feature. Must be one of:
  - "NONE" : no feature weighting
  - "TF_IDF" : TF-IDF weighting
  - "BM_25" : Okapi BM-25 weighting

  Defaults to "NONE".
- **bm25_k1** (*float, optional*) – The k1 parameter for BM25. Ignored if `feature_weighting` is not "BM_25". Defaults to 1.2.
- **bm25_b** (*float, optional*) – The b parameter for BM25. Ignored if `feature_weighting` is not "BM_25". Defaults to 0.75.

- **n_threads** (*Optional[int], optional*) – Specifies the number of threads to use for the computation. If `None`, the environment variable `"IRSPACK_NUM_THREADS_DEFAULT"` will be looked up, and if the variable is not set, it will be set to `os.cpu_count()`. Defaults to None.

__init__(*X_train_all*, *shrinkage=0.0*, *normalize=False*, *top_k=100*, *feature_weighting='NONE'*, *bm25_k1=1.2*, *bm25_b=0.75*, *n_threads=None*)

Parameters

- **X_train_all** (*Union[csr_matrix, csc_matrix]*) –
- **shrinkage** (*float*) –
- **normalize** (*bool*) –
- **top_k** (*int*) –
- **feature_weighting** (*str*) –
- **bm25_k1** (*float*) –
- **bm25_b** (*float*) –
- **n_threads** (*Optional[int]*) –

Return type
None

Methods

__init__(X_train_all[, shrinkage, ...])	
default_suggest_parameter(trial, fixed_params)	
from_config(X_train_all, config)	
get_score(user_indices)	Compute the item recommendation score for a subset of users.
get_score_block(begin, end)	Compute the score for a block of the users.
get_score_cold_user(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_cold_user_remove_seen(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_remove_seen(user_indices)	Compute the item score and mask the item in the training set.
get_score_remove_seen_block(begin, end)	Compute the score for a block of the users, and mask the items in the training set.
learn()	Learns and returns itself.
learn_with_optimizer(evaluator, trial[, ...])	Learning procedures with early stopping and pruning.
tune(data, evaluator[, n_trials, timeout, ...])	Perform the optimization step.
tune_with_study(study, data, evaluator[, ...])	

Attributes

W	The computed item-item similarity weight matrix.
default_tune_range	

property W: Union[csr_matrix, csc_matrix, ndarray]

The computed item-item similarity weight matrix.

X_train_all: sps.csr_matrix

The matrix to feed into recommender.

get_score(*user_indices*)

Compute the item recommendation score for a subset of users.

Parameters
user_indices (*ndarray*) – The index defines the subset of users.

Returns
The item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

get_score_block(*begin*, *end*)

Compute the score for a block of the users.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

get_score_cold_user(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed item scores for users. Its shape is equal to X.

Return type
ndarray

get_score_cold_user_remove_seen(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix. The score will then be masked by the input.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed & masked item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_remove_seen`(*user_indices*)

Compute the item score and mask the item in the training set. Masked items will have the score -inf.

Parameters
user_indices (*ndarray*) – Specifies the subset of users.

Returns
The masked item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

`get_score_remove_seen_block`(*begin*, *end*)

Compute the score for a block of the users, and mask the items in the training set. Masked items will have the score -inf.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The masked item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`learn`()

Learns and returns itself.

Returns
The model after fitting process.

Parameters
self (*R*) –

Return type
R

`learn_with_optimizer`(*evaluator*, *trial*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*)

Learning procedures with early stopping and pruning.

Parameters

- **evaluator** (*Optional[evaluation.Evaluator]*) – The evaluator to measure the score.
- **trial** (*Optional[Trial]*) – The current optuna trial under the study (if any.)
- **max_epoch** (*int*) – Maximal number of epochs. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 128.
- **validate_epoch** (*int*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **validate_epoch** – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

- **score_degradation_max** (*int*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

Return type
None

classmethod tune(*data*, *evaluator*, *n_trials=20*, *timeout=None*, *data_suggest_function=None*, *parameter_suggest_function=None*, *fixed_params={}*, *random_seed=None*, *prunning_n_startup_trials=10*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*, *logger=None*)

Perform the optimization step. *optuna.Study* object is created inside this function.

Parameters

- **data** (*Optional[Union[csr_matrix, csc_matrix]]*) – The training data. You can also provide tunable parameter dependent training data by providing *data_suggest_function*. In that case, data must be *None*.
- **evaluator** (evaluation.Evaluator) – The validation evaluator that measures the performance of the recommenders.
- **n_trials** (*int*) – The number of expected trials (including pruned ones). Defaults to 20.
- **timeout** (*Optional[int]*) – If set to some value (in seconds), the study will exit after that time period. Note that the running trials is not interrupted, though. Defaults to *None*.
- **data_suggest_function** (*Optional[Callable[[Trial], Union[csr_matrix, csc_matrix]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns training data. Defaults to *None*.
- **parameter_suggest_function** (*Optional[Callable[[Trial], Dict[str, Any]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns *Dict[str, Any]* (i.e., some keyword arguments of the recommender class). If *None*, *cls.default_suggest_parameter* will be used for the parameter suggestion. Defaults to *None*.
- **fixed_params** (*Dict[str, Any]*) – Fixed parameters passed to recommenders during the optimization procedure. This will replace the suggested parameter (either by *cls.default_suggest_parameter* or *parameter_suggest_function*). Defaults to *dict()*.
- **random_seed** (*Optional[int]*) – The random seed to control *optuna.samplers.TPESampler*. Defaults to *None*.
- **prunning_n_startup_trials** (*int*) – *n_startup_trials* argument passed to the constructor of *optuna.pruners.MedianPruner*.
- **max_epoch** (*int*) – The maximal number of epochs for the training. If iterative learning procedure is not available, this parameter will be ignored.
- **validate_epoch** (*int, optional*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int, optional*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5. Defaults to 5.
- **logger** (*Optional[Logger]*) –

Returns

A tuple that consists of

1. A dict containing the best paramaters. This dict can be passed to the recommender as `**kwargs`.
2. A `pandas.DataFrame` that contains the history of optimization.

Return type
Tuple[*Dict*[str, *Any*], *DataFrame*]

irspack.recommenders.AsymmetricCosineKNNRecommender

class irspack.recommenders.**AsymmetricCosineKNNRecommender**(*X_train_all*, *shrinkage=0.0*, *alpha=0.5*, *top_k=100*, *feature_weighting='NONE'*, *bm25_k1=1.2*, *bm25_b=0.75*, *n_threads=None*)

Bases: `BaseKNNRecommender`

K-nearest neighbor recommender system based on asymmetric cosine similarity. That is, the similarity matrix `W` is given by (column-wise top-k restricted)

$$\mathrm{W}_{i,j} = \frac{\sum_u X_{ui} X_{uj}}{||X_{*i}||_2^{2\alpha} ||X_{*j}||_2^{2(1-\alpha)} + \mathrm{shrinkage}}$$

Parameters

- **X_train_all** (*Union[scipy.sparse.csr_matrix, scipy.sparse.csc_matrix]*) – Input interaction matrix.
- **shrinkage** (*float, optional*) – The shrinkage parameter for regularization. Defaults to 0.0.
- **alpha** (*bool, optional*) – Specifies α. Defaults to 0.5.
- **top_k** (*int, optional*) – Specifies the maximal number of allowed neighbors. Defaults to 100.
- **feature_weighting** (*str, optional*) – Specifies how to weight the feature. Must be one of:
  - ”NONE” : no feature weighting
  - ”TF_IDF” : TF-IDF weighting
  - ”BM_25” : Okapi BM-25 weighting

  Defaults to “NONE”.
- **bm25_k1** (*float, optional*) – The k1 parameter for BM25. Ignored if `feature_weighting` is not “BM_25”. Defaults to 1.2.
- **bm25_b** (*float, optional*) – The b parameter for BM25. Ignored if `feature_weighting` is not “BM_25”. Defaults to 0.75.
- **n_threads** (*Optional[int], optional*) – Specifies the number of threads to use for the computation. If `None`, the environment variable `"IRSPACK_NUM_THREADS_DEFAULT"` will be looked up, and if the variable is not set, it will be set to `os.cpu_count()`. Defaults to None.

__init__(*X_train_all*, *shrinkage=0.0*, *alpha=0.5*, *top_k=100*, *feature_weighting='NONE'*, *bm25_k1=1.2*, *bm25_b=0.75*, *n_threads=None*)

Parameters

- **X_train_all** (*Union[csr_matrix, csc_matrix]*) –
- **shrinkage** (*float*) –
- **alpha** (*float*) –
- **top_k** (*int*) –
- **feature_weighting** (*str*) –
- **bm25_k1** (*float*) –
- **bm25_b** (*float*) –
- **n_threads** (*Optional[int]*) –

Methods

__init__(X_train_all[, shrinkage, alpha, ...])	
default_suggest_parameter(trial, fixed_params)	
from_config(X_train_all, config)	
get_score(user_indices)	Compute the item recommendation score for a subset of users.
get_score_block(begin, end)	Compute the score for a block of the users.
get_score_cold_user(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_cold_user_remove_seen(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_remove_seen(user_indices)	Compute the item score and mask the item in the training set.
get_score_remove_seen_block(begin, end)	Compute the score for a block of the users, and mask the items in the training set.
learn()	Learns and returns itself.
learn_with_optimizer(evaluator, trial[, ...])	Learning procedures with early stopping and pruning.
tune(data, evaluator[, n_trials, timeout, ...])	Perform the optimization step.
tune_with_study(study, data, evaluator[, ...])	

Attributes

W	The computed item-item similarity weight matrix.
default_tune_range	

property W: Union[csr_matrix, csc_matrix, ndarray]

The computed item-item similarity weight matrix.

X_train_all: sps.csr_matrix

The matrix to feed into recommender.

get_score(*user_indices*)

Compute the item recommendation score for a subset of users.

Parameters
user_indices (*ndarray*) – The index defines the subset of users.

Returns
The item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

get_score_block(*begin*, *end*)

Compute the score for a block of the users.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

get_score_cold_user(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed item scores for users. Its shape is equal to X.

Return type
ndarray

get_score_cold_user_remove_seen(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix. The score will then be masked by the input.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed & masked item scores for users. Its shape is equal to X.

Return type
ndarray

get_score_remove_seen(*user_indices*)

Compute the item score and mask the item in the training set. Masked items will have the score -inf.

Parameters
user_indices (*ndarray*) – Specifies the subset of users.

Returns
The masked item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

`get_score_remove_seen_block`(*begin*, *end*)

Compute the score for a block of the users, and mask the items in the training set. Masked items will have the score -inf.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The masked item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`learn`()

Learns and returns itself.

Returns
The model after fitting process.

Parameters
self (*R*) –

Return type
R

`learn_with_optimizer`(*evaluator*, *trial*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*)

Learning procedures with early stopping and pruning.

Parameters

- **evaluator** (*Optional[evaluation.Evaluator]*) – The evaluator to measure the score.
- **trial** (*Optional[Trial]*) – The current optuna trial under the study (if any.)
- **max_epoch** (*int*) – Maximal number of epochs. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 128.
- **validate_epoch** (*int*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **validate_epoch** – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

Return type
None

`classmethod tune`(*data*, *evaluator*, *n_trials=20*, *timeout=None*, *data_suggest_function=None*, *parameter_suggest_function=None*, *fixed_params={}*, *random_seed=None*, *prunning_n_startup_trials=10*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*, *logger=None*)

Perform the optimization step. *optuna.Study* object is created inside this function.

Parameters

- **data** (*Optional[Union[csr_matrix, csc_matrix]]*) – The training data. You can also provide tunable parameter dependent training data by providing *data_suggest_function*. In that case, data must be *None*.
- **evaluator** (evaluation.Evaluator) – The validation evaluator that measures the performance of the recommenders.
- **n_trials** (*int*) – The number of expected trials (including pruned ones). Defaults to 20.
- **timeout** (*Optional[int]*) – If set to some value (in seconds), the study will exit after that time period. Note that the running trials is not interrupted, though. Defaults to *None*.
- **data_suggest_function** (*Optional[Callable[[Trial], Union[csr_matrix, csc_matrix]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns training data. Defaults to *None*.
- **parameter_suggest_function** (*Optional[Callable[[Trial], Dict[str, Any]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns *Dict[str, Any]* (i.e., some keyword arguments of the recommender class). If *None*, *cls.default_suggest_parameter* will be used for the parameter suggestion. Defaults to *None*.
- **fixed_params** (*Dict[str, Any]*) – Fixed parameters passed to recommenders during the optimization procedure. This will replace the suggested parameter (either by *cls.default_suggest_parameter* or *parameter_suggest_function*). Defaults to *dict()*.
- **random_seed** (*Optional[int]*) – The random seed to control *optuna.samplers.TPESampler*. Defaults to *None*.
- **prunning_n_startup_trials** (*int*) – *n_startup_trials* argument passed to the constructor of *optuna.pruners.MedianPruner*.
- **max_epoch** (*int*) – The maximal number of epochs for the training. If iterative learning procedure is not available, this parameter will be ignored.
- **validate_epoch** (*int, optional*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int, optional*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5. Defaults to 5.
- **logger** (*Optional[Logger]*) –

Returns

A tuple that consists of

1. A dict containing the best paramaters. This dict can be passed to the recommender as `**kwargs`.
2. A `pandas.DataFrame` that contains the history of optimization.

Return type

Tuple[*Dict*[str, *Any*], *DataFrame*]

irspack.recommenders.JaccardKNNRecommender

class irspack.recommenders.**JaccardKNNRecommender**(*X_train_all*, *shrinkage=0.0*, *top_k=100*, *n_threads=None*)

Bases: BaseKNNRecommender

K-nearest neighbor recommender system based on Jaccard similarity. That is, the similarity matrix W is given by (column-wise top-k restricted)

$$\mathrm{W}_{i,j} = \frac{|U_i \cap U_j|}{|U_i \cup U_j| + \mathrm{shrinkage}}$$

Parameters

- **X_train_all** (*Union[scipy.sparse.csr_matrix, scipy.sparse.csc_matrix]*) – Input interaction matrix.
- **shrinkage** (*float, optional*) – The shrinkage parameter for regularization. Defaults to 0.0.
- **top_k** (*int, optional*) – Specifies the maximal number of allowed neighbors. Defaults to 100.
- **n_threads** (*Optional[int], optional*) – Specifies the number of threads to use for the computation. If None, the environment variable "IRSPACK_NUM_THREADS_DEFAULT" will be looked up, and if the variable is not set, it will be set to os.cpu_count(). Defaults to None.

__init__(*X_train_all*, *shrinkage=0.0*, *top_k=100*, *n_threads=None*)

Parameters

- **X_train_all** (*Union[csr_matrix, csc_matrix]*) –
- **shrinkage** (*float*) –
- **top_k** (*int*) –
- **n_threads** (*Optional[int]*) –

Return type
None

Methods

__init__(X_train_all[, shrinkage, top_k, ...])	
default_suggest_parameter(trial, fixed_params)	
from_config(X_train_all, config)	
get_score(user_indices)	Compute the item recommendation score for a subset of users.
get_score_block(begin, end)	Compute the score for a block of the users.
get_score_cold_user(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_cold_user_remove_seen(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_remove_seen(user_indices)	Compute the item score and mask the item in the training set.
get_score_remove_seen_block(begin, end)	Compute the score for a block of the users, and mask the items in the training set.
learn()	Learns and returns itself.
learn_with_optimizer(evaluator, trial[, ...])	Learning procedures with early stopping and pruning.
tune(data, evaluator[, n_trials, timeout, ...])	Perform the optimization step.
tune_with_study(study, data, evaluator[, ...])	

Attributes

W	The computed item-item similarity weight matrix.
default_tune_range	

property W: Union[csr_matrix, csc_matrix, ndarray]

The computed item-item similarity weight matrix.

X_train_all: sps.csr_matrix

The matrix to feed into recommender.

get_score(*user_indices*)

Compute the item recommendation score for a subset of users.

Parameters
user_indices (*ndarray*) – The index defines the subset of users.

Returns
The item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

get_score_block(*begin*, *end*)

Compute the score for a block of the users.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

get_score_cold_user(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed item scores for users. Its shape is equal to X.

Return type
ndarray

get_score_cold_user_remove_seen(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix. The score will then be masked by the input.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed & masked item scores for users. Its shape is equal to X.

Return type
ndarray

get_score_remove_seen(*user_indices*)

Compute the item score and mask the item in the training set. Masked items will have the score -inf.

Parameters
user_indices (*ndarray*) – Specifies the subset of users.

Returns
The masked item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

get_score_remove_seen_block(*begin*, *end*)

Compute the score for a block of the users, and mask the items in the training set. Masked items will have the score -inf.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The masked item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`learn`()

Learns and returns itself.

Returns
The model after fitting process.

Parameters
self (*R*) –

Return type
R

`learn_with_optimizer`(*evaluator*, *trial*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*)

Learning procedures with early stopping and pruning.

Parameters

- **evaluator** (*Optional[evaluation.Evaluator]*) – The evaluator to measure the score.
- **trial** (*Optional[Trial]*) – The current optuna trial under the study (if any.)
- **max_epoch** (*int*) – Maximal number of epochs. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 128.
- **validate_epoch** (*int*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **validate_epoch** – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

Return type
None

`classmethod tune`(*data*, *evaluator*, *n_trials=20*, *timeout=None*, *data_suggest_function=None*, *parameter_suggest_function=None*, *fixed_params={}*, *random_seed=None*, *prunning_n_startup_trials=10*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*, *logger=None*)

Perform the optimization step. *optuna.Study* object is created inside this function.

Parameters

- **data** (*Optional[Union[csr_matrix, csc_matrix]]*) – The training data. You can also provide tunable parameter dependent training data by providing *data_suggest_function*. In that case, data must be *None*.
- **evaluator** (*evaluation.Evaluator*) – The validation evaluator that measures the performance of the recommenders.
- **n_trials** (*int*) – The number of expected trials (including pruned ones). Defaults to 20.
- **timeout** (*Optional[int]*) – If set to some value (in seconds), the study will exit after that time period. Note that the running trials is not interrupted, though. Defaults to *None*.
- **data_suggest_function** (*Optional[Callable[[Trial], Union[csr_matrix, csc_matrix]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns training data. Defaults to *None*.

- **parameter_suggest_function** (*Optional[Callable[[Trial], Dict[str, Any]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns *Dict[str, Any]* (i.e., some keyword arguments of the recommender class). If *None*, *cls.default_suggest_parameter* will be used for the parameter suggestion. Defaults to *None*.
- **fixed_params** (*Dict[str, Any]*) – Fixed parameters passed to recommenders during the optimization procedure. This will replace the suggested parameter (either by *cls.default_suggest_parameter* or *parameter_suggest_function*). Defaults to *dict()*.
- **random_seed** (*Optional[int]*) – The random seed to control *optuna.samplers.TPESampler*. Defaults to *None*.
- **prunning_n_startup_trials** (*int*) – *n_startup_trials* argument passed to the constructor of *optuna.pruners.MedianPruner*.
- **max_epoch** (*int*) – The maximal number of epochs for the training. If iterative learning procedure is not available, this parameter will be ignored.
- **validate_epoch** (*int, optional*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int, optional*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5. Defaults to 5.
- **logger** (*Optional[Logger]*) –

Returns

A tuple that consists of

1. A dict containing the best paramaters. This dict can be passed to the recommender as `**kwargs`.
2. A `pandas.DataFrame` that contains the history of optimization.

Return type
Tuple[*Dict*[str, *Any*], *DataFrame*]

irspack.recommenders.TverskyIndexKNNRecommender

class irspack.recommenders.**TverskyIndexKNNRecommender**(*X_train_all*, *shrinkage=0.0*, *alpha=0.5*, *beta=0.5*, *top_k=100*, *n_threads=None*)

Bases: `BaseKNNRecommender`

K-nearest neighbor recommender system based on Tversky Index. That is, the similarity matrix `W` is given by (column-wise top-k restricted)

$$\mathrm{W}_{i,j} = \frac{|U_i \cap U_j|}{|U_i \cap U_j| + \alpha |U_i \setminus U_j| + \beta |U_j \setminus U_i| + \mathrm{shrinkage}}$$

Parameters

- **X_train_all** (*Union[scipy.sparse.csr_matrix, scipy.sparse.csc_matrix]*) – Input interaction matrix.
- **shrinkage** (*float, optional*) – The shrinkage parameter for regularization. Defaults to 0.0.

- **alpha** (*float, optional*) – $alpha$ parameter. Defaults to 0.5.
- **beta** (*float, optional*) – $beta$ parameter. Defaults to 0.5.
- **top_k** (*int, optional*) – Specifies the maximal number of allowed neighbors. Defaults to 100.
- **n_threads** (*Optional[int], optional*) – Specifies the number of threads to use for the computation. If `None`, the environment variable `"IRSPACK_NUM_THREADS_DEFAULT"` will be looked up, and if the variable is not set, it will be set to `os.cpu_count()`. Defaults to None.

__init__(*X_train_all*, *shrinkage=0.0*, *alpha=0.5*, *beta=0.5*, *top_k=100*, *n_threads=None*)

Parameters

- **X_train_all** (*Union[csr_matrix, csc_matrix]*) –
- **shrinkage** (*float*) –
- **alpha** (*float*) –
- **beta** (*float*) –
- **top_k** (*int*) –
- **n_threads** (*Optional[int]*) –

Return type
None

Methods

__init__(X_train_all[, shrinkage, alpha, ...])	
default_suggest_parameter(trial, fixed_params)	
from_config(X_train_all, config)	
get_score(user_indices)	Compute the item recommendation score for a subset of users.
get_score_block(begin, end)	Compute the score for a block of the users.
get_score_cold_user(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_cold_user_remove_seen(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_remove_seen(user_indices)	Compute the item score and mask the item in the training set.
get_score_remove_seen_block(begin, end)	Compute the score for a block of the users, and mask the items in the training set.
learn()	Learns and returns itself.
learn_with_optimizer(evaluator, trial[, ...])	Learning procedures with early stopping and pruning.
tune(data, evaluator[, n_trials, timeout, ...])	Perform the optimization step.
tune_with_study(study, data, evaluator[, ...])	

Attributes

W	The computed item-item similarity weight matrix.
default_tune_range	

property W: Union[csr_matrix, csc_matrix, ndarray]

The computed item-item similarity weight matrix.

X_train_all: sps.csr_matrix

The matrix to feed into recommender.

get_score(*user_indices*)

Compute the item recommendation score for a subset of users.

Parameters
user_indices (*ndarray*) – The index defines the subset of users.

Returns
The item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

get_score_block(*begin*, *end*)

Compute the score for a block of the users.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

get_score_cold_user(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed item scores for users. Its shape is equal to X.

Return type
ndarray

get_score_cold_user_remove_seen(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix. The score will then be masked by the input.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed & masked item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_remove_seen`(*user_indices*)

Compute the item score and mask the item in the training set. Masked items will have the score -inf.

Parameters
user_indices (*ndarray*) – Specifies the subset of users.

Returns
The masked item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

`get_score_remove_seen_block`(*begin*, *end*)

Compute the score for a block of the users, and mask the items in the training set. Masked items will have the score -inf.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The masked item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`learn`()

Learns and returns itself.

Returns
The model after fitting process.

Parameters
self (*R*) –

Return type
R

`learn_with_optimizer`(*evaluator*, *trial*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*)

Learning procedures with early stopping and pruning.

Parameters

- **evaluator** (*Optional[evaluation.Evaluator]*) – The evaluator to measure the score.
- **trial** (*Optional[Trial]*) – The current optuna trial under the study (if any.)
- **max_epoch** (*int*) – Maximal number of epochs. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 128.
- **validate_epoch** (*int*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **validate_epoch** – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

- **score_degradation_max** (*int*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

Return type
None

classmethod tune(*data*, *evaluator*, *n_trials=20*, *timeout=None*, *data_suggest_function=None*, *parameter_suggest_function=None*, *fixed_params={}*, *random_seed=None*, *prunning_n_startup_trials=10*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*, *logger=None*)

Perform the optimization step. *optuna.Study* object is created inside this function.

Parameters

- **data** (*Optional[Union[csr_matrix, csc_matrix]]*) – The training data. You can also provide tunable parameter dependent training data by providing *data_suggest_function*. In that case, data must be *None*.
- **evaluator** (evaluation.Evaluator) – The validation evaluator that measures the performance of the recommenders.
- **n_trials** (*int*) – The number of expected trials (including pruned ones). Defaults to 20.
- **timeout** (*Optional[int]*) – If set to some value (in seconds), the study will exit after that time period. Note that the running trials is not interrupted, though. Defaults to *None*.
- **data_suggest_function** (*Optional[Callable[[Trial], Union[csr_matrix, csc_matrix]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns training data. Defaults to *None*.
- **parameter_suggest_function** (*Optional[Callable[[Trial], Dict[str, Any]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns *Dict[str, Any]* (i.e., some keyword arguments of the recommender class). If *None*, *cls.default_suggest_parameter* will be used for the parameter suggestion. Defaults to *None*.
- **fixed_params** (*Dict[str, Any]*) – Fixed parameters passed to recommenders during the optimization procedure. This will replace the suggested parameter (either by *cls.default_suggest_parameter* or *parameter_suggest_function*). Defaults to *dict()*.
- **random_seed** (*Optional[int]*) – The random seed to control *optuna.samplers.TPESampler*. Defaults to *None*.
- **prunning_n_startup_trials** (*int*) – *n_startup_trials* argument passed to the constructor of *optuna.pruners.MedianPruner*.
- **max_epoch** (*int*) – The maximal number of epochs for the training. If iterative learning procedure is not available, this parameter will be ignored.
- **validate_epoch** (*int, optional*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int, optional*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5. Defaults to 5.
- **logger** (*Optional[Logger]*) –

Returns

A tuple that consists of

1. A dict containing the best paramaters. This dict can be passed to the recommender as `**kwargs`.
2. A `pandas.DataFrame` that contains the history of optimization.

Return type
Tuple[*Dict*[str, *Any*], *DataFrame*]

irspack.recommenders.CosineUserKNNRecommender

class irspack.recommenders.**CosineUserKNNRecommender**(*X_train_all*, *shrinkage=0.0*, *normalize=True*, *top_k=100*, *feature_weighting='NONE'*, *bm25_k1=1.2*, *bm25_b=0.75*, *n_threads=None*)

Bases: `BaseUserKNNRecommender`

K-nearest neighbor recommender system based on cosine similarity. That is, the similarity matrix `U` is given by (row-wise top-k restricted)

$$\mathrm{U}_{u,v} = \begin{cases} \frac{\sum_i X_{ui} X_{vi}}{||X_{u*}||_2 ||X_{v*}||_2 + \mathrm{shrinkage}} & \text{(if normalize = True)} \\ \sum_i X_{ui} X_{vi} & \text{(if normalize = False)} \end{cases}$$

Parameters

- **X_train_all** (*Union[scipy.sparse.csr_matrix, scipy.sparse.csc_matrix]*) – Input interaction matrix.
- **shrinkage** (*float, optional*) – The shrinkage parameter for regularization. Defaults to 0.0.
- **normalize** (*bool, optional*) – Whether to normalize the similarity. Defaults to False.
- **top_k** (*int, optional*) – Specifies the maximal number of allowed neighbors. Defaults to 100.
- **feature_weighting** (*str, optional*) – Specifies how to weight the feature. Must be one of:
  - ”NONE” : no feature weighting
  - ”TF_IDF” : TF-IDF weighting
  - ”BM_25” : Okapi BM-25 weighting

  Defaults to “NONE”.
- **bm25_k1** (*float, optional*) – The k1 parameter for BM25. Ignored if `feature_weighting` is not “BM_25”. Defaults to 1.2.
- **bm25_b** (*float, optional*) – The b parameter for BM25. Ignored if `feature_weighting` is not “BM_25”. Defaults to 0.75.
- **n_threads** (*Optional[int], optional*) – Specifies the number of threads to use for the computation. If `None`, the environment variable `"IRSPACK_NUM_THREADS_DEFAULT"` will be looked up, and if the variable is not set, it will be set to `os.cpu_count()`. Defaults to None.

__init__(*X_train_all*, *shrinkage=0.0*, *normalize=True*, *top_k=100*, *feature_weighting='NONE'*, *bm25_k1=1.2*, *bm25_b=0.75*, *n_threads=None*)

Parameters

- **X_train_all** (*Union[csr_matrix, csc_matrix]*) –

- **shrinkage** (*float*) –
- **normalize** (*bool*) –
- **top_k** (*int*) –
- **feature_weighting** (*str*) –
- **bm25_k1** (*float*) –
- **bm25_b** (*float*) –
- **n_threads** (*Optional[int]*) –

Methods

__init__(X_train_all[, shrinkage, ...])	
default_suggest_parameter(trial, fixed_params)	
from_config(X_train_all, config)	
get_score(user_indices)	Compute the item recommendation score for a subset of users.
get_score_block(begin, end)	Compute the score for a block of the users.
get_score_cold_user(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_cold_user_remove_seen(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_remove_seen(user_indices)	Compute the item score and mask the item in the training set.
get_score_remove_seen_block(begin, end)	Compute the score for a block of the users, and mask the items in the training set.
learn()	Learns and returns itself.
learn_with_optimizer(evaluator, trial[, ...])	Learning procedures with early stopping and pruning.
tune(data, evaluator[, n_trials, timeout, ...])	Perform the optimization step.
tune_with_study(study, data, evaluator[, ...])	

Attributes

U	The computed user-user similarity weight matrix.
default_tune_range	

property U: Union[csr_matrix, csc_matrix, ndarray]

The computed user-user similarity weight matrix.

X_train_all: sps.csr_matrix

The matrix to feed into recommender.

`get_score`(*user_indices*)

Compute the item recommendation score for a subset of users.

Parameters
user_indices (*ndarray*) – The index defines the subset of users.

Returns
The item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

`get_score_block`(*begin*, *end*)

Compute the score for a block of the users.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`get_score_cold_user`(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_cold_user_remove_seen`(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix. The score will then be masked by the input.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed & masked item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_remove_seen`(*user_indices*)

Compute the item score and mask the item in the training set. Masked items will have the score -inf.

Parameters
user_indices (*ndarray*) – Specifies the subset of users.

Returns
The masked item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

`get_score_remove_seen_block`(*begin*, *end*)

Compute the score for a block of the users, and mask the items in the training set. Masked items will have the score -inf.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The masked item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`learn`()

Learns and returns itself.

Returns
The model after fitting process.

Parameters
self (*R*) –

Return type
R

`learn_with_optimizer`(*evaluator*, *trial*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*)

Learning procedures with early stopping and pruning.

Parameters

- **evaluator** (*Optional[evaluation.Evaluator]*) – The evaluator to measure the score.
- **trial** (*Optional[Trial]*) – The current optuna trial under the study (if any.)
- **max_epoch** (*int*) – Maximal number of epochs. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 128.
- **validate_epoch** (*int*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **validate_epoch** – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

Return type
None

`classmethod tune`(*data*, *evaluator*, *n_trials=20*, *timeout=None*, *data_suggest_function=None*, *parameter_suggest_function=None*, *fixed_params={}*, *random_seed=None*, *prunning_n_startup_trials=10*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*, *logger=None*)

Perform the optimization step. *optuna.Study* object is created inside this function.

Parameters

- **data** (*Optional[Union[csr_matrix, csc_matrix]]*) – The training data. You can also provide tunable parameter dependent training data by providing *data_suggest_function*. In that case, data must be *None*.
- **evaluator** (evaluation.Evaluator) – The validation evaluator that measures the performance of the recommenders.
- **n_trials** (*int*) – The number of expected trials (including pruned ones). Defaults to 20.
- **timeout** (*Optional[int]*) – If set to some value (in seconds), the study will exit after that time period. Note that the running trials is not interrupted, though. Defaults to *None*.
- **data_suggest_function** (*Optional[Callable[[Trial], Union[csr_matrix, csc_matrix]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns training data. Defaults to *None*.
- **parameter_suggest_function** (*Optional[Callable[[Trial], Dict[str, Any]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns *Dict[str, Any]* (i.e., some keyword arguments of the recommender class). If *None*, *cls.default_suggest_parameter* will be used for the parameter suggestion. Defaults to *None*.
- **fixed_params** (*Dict[str, Any]*) – Fixed parameters passed to recommenders during the optimization procedure. This will replace the suggested parameter (either by *cls.default_suggest_parameter* or *parameter_suggest_function*). Defaults to *dict()*.
- **random_seed** (*Optional[int]*) – The random seed to control *optuna.samplers.TPESampler*. Defaults to *None*.
- **prunning_n_startup_trials** (*int*) – *n_startup_trials* argument passed to the constructor of *optuna.pruners.MedianPruner*.
- **max_epoch** (*int*) – The maximal number of epochs for the training. If iterative learning procedure is not available, this parameter will be ignored.
- **validate_epoch** (*int, optional*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int, optional*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5. Defaults to 5.
- **logger** (*Optional[Logger]*) –

Returns

A tuple that consists of

1. A dict containing the best paramaters. This dict can be passed to the recommender as `**kwargs`.
2. A `pandas.DataFrame` that contains the history of optimization.

Return type

Tuple[*Dict*[str, *Any*], *DataFrame*]

irspack.recommenders.AsymmetricCosineUserKNNRecommender

class irspack.recommenders.**AsymmetricCosineUserKNNRecommender**(*X_train_all*, *shrinkage=0.0*, *alpha=0.5*, *top_k=100*, *feature_weighting='NONE'*, *bm25_k1=1.2*, *bm25_b=0.75*, *n_threads=None*)

Bases: `BaseUserKNNRecommender`

K-nearest neighbor recommender system based on asymmetric cosine similarity. That is, the similarity matrix `U` is given by (row-wise top-k restricted)

$$\mathrm{U}_{u,v} = \frac{\sum_i X_{ui} X_{vi}}{||X_{u*}||_2^{2\alpha} ||X_{v*}||_2^{2(1-\alpha)} + \mathrm{shrinkage}}$$

Parameters

- **X_train_all** (*Union[scipy.sparse.csr_matrix, scipy.sparse.csc_matrix]*) – Input interaction matrix.
- **shrinkage** (*float, optional*) – The shrinkage parameter for regularization. Defaults to 0.0.
- **alpha** (*bool, optional*) – Specifies α. Defaults to 0.5.
- **top_k** (*int, optional*) – Specifies the maximal number of allowed neighbors. Defaults to 100.
- **feature_weighting** (*str, optional*) – Specifies how to weight the feature. Must be one of:
  - "NONE" : no feature weighting
  - "TF_IDF" : TF-IDF weighting
  - "BM_25" : Okapi BM-25 weighting

  Defaults to "NONE".
- **bm25_k1** (*float, optional*) – The k1 parameter for BM25. Ignored if `feature_weighting` is not "BM_25". Defaults to 1.2.
- **bm25_b** (*float, optional*) – The b parameter for BM25. Ignored if `feature_weighting` is not "BM_25". Defaults to 0.75.
- **n_threads** (*Optional[int], optional*) – Specifies the number of threads to use for the computation. If `None`, the environment variable `"IRSPACK_NUM_THREADS_DEFAULT"` will be looked up, and if the variable is not set, it will be set to `os.cpu_count()`. Defaults to None.

__init__(*X_train_all*, *shrinkage=0.0*, *alpha=0.5*, *top_k=100*, *feature_weighting='NONE'*, *bm25_k1=1.2*, *bm25_b=0.75*, *n_threads=None*)

Parameters

- **X_train_all** (*Union[csr_matrix, csc_matrix]*) –
- **shrinkage** (*float*) –
- **alpha** (*float*) –
- **top_k** (*int*) –
- **feature_weighting** (*str*) –

- **bm25_k1** (*float*) –
- **bm25_b** (*float*) –
- **n_threads** (*Optional[int]*) –

Methods

__init__(X_train_all[, shrinkage, alpha, ...])	
default_suggest_parameter(trial, fixed_params)	
from_config(X_train_all, config)	
get_score(user_indices)	Compute the item recommendation score for a subset of users.
get_score_block(begin, end)	Compute the score for a block of the users.
get_score_cold_user(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_cold_user_remove_seen(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_remove_seen(user_indices)	Compute the item score and mask the item in the training set.
get_score_remove_seen_block(begin, end)	Compute the score for a block of the users, and mask the items in the training set.
learn()	Learns and returns itself.
learn_with_optimizer(evaluator, trial[, ...])	Learning procedures with early stopping and pruning.
tune(data, evaluator[, n_trials, timeout, ...])	Perform the optimization step.
tune_with_study(study, data, evaluator[, ...])	

Attributes

U	The computed user-user similarity weight matrix.
default_tune_range	

property U: Union[csr_matrix, csc_matrix, ndarray]

The computed user-user similarity weight matrix.

X_train_all: sps.csr_matrix

The matrix to feed into recommender.

get_score(*user_indices*)

Compute the item recommendation score for a subset of users.

Parameters

user_indices (*ndarray*) – The index defines the subset of users.

Returns

The item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

`get_score_block`(*begin*, *end*)

Compute the score for a block of the users.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`get_score_cold_user`(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_cold_user_remove_seen`(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix. The score will then be masked by the input.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed & masked item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_remove_seen`(*user_indices*)

Compute the item score and mask the item in the training set. Masked items will have the score -inf.

Parameters
user_indices (*ndarray*) – Specifies the subset of users.

Returns
The masked item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

`get_score_remove_seen_block`(*begin*, *end*)

Compute the score for a block of the users, and mask the items in the training set. Masked items will have the score -inf.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The masked item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

learn()

Learns and returns itself.

Returns
The model after fitting process.

Parameters
self (*R*) –

Return type
R

learn_with_optimizer(*evaluator*, *trial*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*)

Learning procedures with early stopping and pruning.

Parameters

- **evaluator** (*Optional[evaluation.Evaluator]*) – The evaluator to measure the score.
- **trial** (*Optional[Trial]*) – The current optuna trial under the study (if any.)
- **max_epoch** (*int*) – Maximal number of epochs. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 128.
- **validate_epoch** (*int*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **validate_epoch** – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

Return type
None

classmethod tune(*data*, *evaluator*, *n_trials=20*, *timeout=None*, *data_suggest_function=None*, *parameter_suggest_function=None*, *fixed_params={}*, *random_seed=None*, *prunning_n_startup_trials=10*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*, *logger=None*)

Perform the optimization step. *optuna.Study* object is created inside this function.

Parameters

- **data** (*Optional[Union[csr_matrix, csc_matrix]]*) – The training data. You can also provide tunable parameter dependent training data by providing *data_suggest_function*. In that case, data must be *None*.
- **evaluator** (*evaluation.Evaluator*) – The validation evaluator that measures the performance of the recommenders.
- **n_trials** (*int*) – The number of expected trials (including pruned ones). Defaults to 20.

- **timeout** (*Optional[int]*) – If set to some value (in seconds), the study will exit after that time period. Note that the running trials is not interrupted, though. Defaults to *None*.
- **data_suggest_function** (*Optional[Callable[[Trial], Union[csr_matrix, csc_matrix]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns training data. Defaults to *None*.
- **parameter_suggest_function** (*Optional[Callable[[Trial], Dict[str, Any]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns *Dict[str, Any]* (i.e., some keyword arguments of the recommender class). If *None*, *cls.default_suggest_parameter* will be used for the parameter suggestion. Defaults to *None*.
- **fixed_params** (*Dict[str, Any]*) – Fixed parameters passed to recommenders during the optimization procedure. This will replace the suggested parameter (either by *cls.default_suggest_parameter* or *parameter_suggest_function*). Defaults to *dict()*.
- **random_seed** (*Optional[int]*) – The random seed to control *optuna.samplers.TPESampler*. Defaults to *None*.
- **prunning_n_startup_trials** (*int*) – *n_startup_trials* argument passed to the constructor of *optuna.pruners.MedianPruner*.
- **max_epoch** (*int*) – The maximal number of epochs for the training. If iterative learning procedure is not available, this parameter will be ignored.
- **validate_epoch** (*int, optional*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int, optional*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5. Defaults to 5.
- **logger** (*Optional[Logger]*) –

Returns

A tuple that consists of

1. A dict containing the best paramaters. This dict can be passed to the recommender as `**kwargs`.
2. A `pandas.DataFrame` that contains the history of optimization.

Return type
Tuple[*Dict*[str, *Any*], *DataFrame*]

irspack.recommenders.SLIMRecommender

class irspack.recommenders.**SLIMRecommender**(*X_train_all*, *alpha=0.05*, *l1_ratio=0.01*, *positive_only=True*, *n_iter=100*, *tol=0.0001*, *top_k=None*, *n_threads=None*)

Bases: `BaseSimilarityRecommender`

SLIM with ElasticNet-type loss function:

$$\text{loss} = \frac{1}{2}||X - XB||_F^2 + \frac{\alpha(1-l_1)U}{2}||B||_F^2 F + \alpha l_1 U|B|$$

The implementation relies on a simple (parallelized) cyclic-coordinate descent method.

Parameters

- **X_train_all** (*csr_matrix*) – Input interaction matrix.
- **alpha** (*float*) – Determines the strength of L1/L2 regularization (see above). Defaults to 0.05.
- **l1_ratio** (*float*) – Determines the strength of L1 regularization relative to alpha. Defaults to 0.01.
- **positive_only** (*bool*) – Whether we constrain the weight matrix to be non-negative. Defaults to True.
- **n_iter** (*int*) – The number of coordinate-descent iterations. Defaults to 100.
- **tol** (*float*) – Tolerance parameter for cd iteration, i.e., if the maximal parameter change of the coordinate-descent single iteration is smaller than this value, the iteration will terminate. Defaults to 1e-4.
- **top_k** (*Optional[int]*) – Specifies the maximal number of allowed non-zero coefficients per item. Defaults to None.
- **n_threads** (*Optional[int]*) – Specifies the number of threads to use for the computation. If `None`, the environment variable `"IRSPACK_NUM_THREADS_DEFAULT"` will be looked up, and if the variable is not set, it will be set to `os.cpu_count()`. Defaults to None.

__init__(*X_train_all*, *alpha=0.05*, *l1_ratio=0.01*, *positive_only=True*, *n_iter=100*, *tol=0.0001*, *top_k=None*, *n_threads=None*)

Parameters

- **X_train_all** (*Union[csr_matrix, csc_matrix]*) –
- **alpha** (*float*) –
- **l1_ratio** (*float*) –
- **positive_only** (*bool*) –
- **n_iter** (*int*) –
- **tol** (*float*) –
- **top_k** (*Optional[int]*) –
- **n_threads** (*Optional[int]*) –

Methods

__init__(X_train_all[, alpha, l1_ratio, ...])	
default_suggest_parameter(trial, fixed_params)	
from_config(X_train_all, config)	
get_score(user_indices)	Compute the item recommendation score for a subset of users.
get_score_block(begin, end)	Compute the score for a block of the users.
get_score_cold_user(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_cold_user_remove_seen(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_remove_seen(user_indices)	Compute the item score and mask the item in the training set.
get_score_remove_seen_block(begin, end)	Compute the score for a block of the users, and mask the items in the training set.
learn()	Learns and returns itself.
learn_with_optimizer(evaluator, trial[, ...])	Learning procedures with early stopping and pruning.
tune(data, evaluator[, n_trials, timeout, ...])	Perform the optimization step.
tune_with_study(study, data, evaluator[, ...])	

Attributes

W	The computed item-item similarity weight matrix.
default_tune_range	

property W: Union[csr_matrix, csc_matrix, ndarray]

The computed item-item similarity weight matrix.

X_train_all: sps.csr_matrix

The matrix to feed into recommender.

get_score(*user_indices*)

Compute the item recommendation score for a subset of users.

Parameters
user_indices (*ndarray*) – The index defines the subset of users.

Returns
The item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

get_score_block(*begin*, *end*)

Compute the score for a block of the users.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

get_score_cold_user(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed item scores for users. Its shape is equal to X.

Return type
ndarray

get_score_cold_user_remove_seen(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix. The score will then be masked by the input.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed & masked item scores for users. Its shape is equal to X.

Return type
ndarray

get_score_remove_seen(*user_indices*)

Compute the item score and mask the item in the training set. Masked items will have the score -inf.

Parameters
user_indices (*ndarray*) – Specifies the subset of users.

Returns
The masked item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

get_score_remove_seen_block(*begin*, *end*)

Compute the score for a block of the users, and mask the items in the training set. Masked items will have the score -inf.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The masked item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`learn`()

Learns and returns itself.

Returns
The model after fitting process.

Parameters
self (*R*) –

Return type
R

`learn_with_optimizer`(*evaluator*, *trial*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*)

Learning procedures with early stopping and pruning.

Parameters

- **evaluator** (*Optional[evaluation.Evaluator]*) – The evaluator to measure the score.
- **trial** (*Optional[Trial]*) – The current optuna trial under the study (if any.)
- **max_epoch** (*int*) – Maximal number of epochs. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 128.
- **validate_epoch** (*int*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **validate_epoch** – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

Return type
None

`classmethod tune`(*data*, *evaluator*, *n_trials=20*, *timeout=None*, *data_suggest_function=None*, *parameter_suggest_function=None*, *fixed_params={}*, *random_seed=None*, *prunning_n_startup_trials=10*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*, *logger=None*)

Perform the optimization step. *optuna.Study* object is created inside this function.

Parameters

- **data** (*Optional[Union[csr_matrix, csc_matrix]]*) – The training data. You can also provide tunable parameter dependent training data by providing *data_suggest_function*. In that case, data must be *None*.
- **evaluator** (*evaluation.Evaluator*) – The validation evaluator that measures the performance of the recommenders.
- **n_trials** (*int*) – The number of expected trials (including pruned ones). Defaults to 20.
- **timeout** (*Optional[int]*) – If set to some value (in seconds), the study will exit after that time period. Note that the running trials is not interrupted, though. Defaults to *None*.
- **data_suggest_function** (*Optional[Callable[[Trial], Union[csr_matrix, csc_matrix]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns training data. Defaults to *None*.

- **parameter_suggest_function** (*Optional[Callable[[Trial], Dict[str, Any]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns *Dict[str, Any]* (i.e., some keyword arguments of the recommender class). If *None*, *cls.default_suggest_parameter* will be used for the parameter suggestion. Defaults to *None*.
- **fixed_params** (*Dict[str, Any]*) – Fixed parameters passed to recommenders during the optimization procedure. This will replace the suggested parameter (either by *cls.default_suggest_parameter* or *parameter_suggest_function*). Defaults to *dict()*.
- **random_seed** (*Optional[int]*) – The random seed to control *optuna.samplers.TPESampler*. Defaults to *None*.
- **prunning_n_startup_trials** (*int*) – *n_startup_trials* argument passed to the constructor of *optuna.pruners.MedianPruner*.
- **max_epoch** (*int*) – The maximal number of epochs for the training. If iterative learning procedure is not available, this parameter will be ignored.
- **validate_epoch** (*int, optional*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int, optional*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5. Defaults to 5.
- **logger** (*Optional[Logger]*) –

Returns

A tuple that consists of

1. A dict containing the best paramaters. This dict can be passed to the recommender as `**kwargs`.
2. A `pandas.DataFrame` that contains the history of optimization.

Return type
Tuple[*Dict*[str, *Any*], *DataFrame*]

irspack.recommenders.DenseSLIMRecommender

class irspack.recommenders.**DenseSLIMRecommender**(*X_train_all*, *reg=1*)

Bases: `BaseSimilarityRecommender`

Implementation of DenseSLIM or Embarrassingly Shallow AutoEncoder (EASE ^R).

See:

- Embarrassingly Shallow Autoencoders for Sparse Data

Parameters

- **X_train_all** (*Union[scipy.sparse.csr_matrix, scipy.sparse.csc_matrix]*) – Input interaction matrix.
- **reg** (*float, optional*) – The regularization parameter for ease. Defaults to 1.0.

__init__(*X_train_all*, *reg=1*)

Parameters

- **X_train_all** (*Union[csr_matrix, csc_matrix]*) –
- **reg** (*float*) –

Methods

__init__(X_train_all[, reg])	
default_suggest_parameter(trial, fixed_params)	
from_config(X_train_all, config)	
get_score(user_indices)	Compute the item recommendation score for a subset of users.
get_score_block(begin, end)	Compute the score for a block of the users.
get_score_cold_user(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_cold_user_remove_seen(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_remove_seen(user_indices)	Compute the item score and mask the item in the training set.
get_score_remove_seen_block(begin, end)	Compute the score for a block of the users, and mask the items in the training set.
learn()	Learns and returns itself.
learn_with_optimizer(evaluator, trial[, ...])	Learning procedures with early stopping and pruning.
tune(data, evaluator[, n_trials, timeout, ...])	Perform the optimization step.
tune_with_study(study, data, evaluator[, ...])	

Attributes

W	The computed item-item similarity weight matrix.
default_tune_range	

property W: Union[csr_matrix, csc_matrix, ndarray]

The computed item-item similarity weight matrix.

X_train_all: sps.csr_matrix

The matrix to feed into recommender.

get_score(*user_indices*)

Compute the item recommendation score for a subset of users.

Parameters

user_indices (*ndarray*) – The index defines the subset of users.

Returns
The item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

`get_score_block`(*begin*, *end*)

Compute the score for a block of the users.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`get_score_cold_user`(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_cold_user_remove_seen`(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix. The score will then be masked by the input.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed & masked item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_remove_seen`(*user_indices*)

Compute the item score and mask the item in the training set. Masked items will have the score -inf.

Parameters
user_indices (*ndarray*) – Specifies the subset of users.

Returns
The masked item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

get_score_remove_seen_block(*begin*, *end*)

Compute the score for a block of the users, and mask the items in the training set. Masked items will have the score -inf.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The masked item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

learn()

Learns and returns itself.

Returns
The model after fitting process.

Parameters
self (*R*) –

Return type
R

learn_with_optimizer(*evaluator*, *trial*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*)

Learning procedures with early stopping and pruning.

Parameters

- **evaluator** (*Optional[evaluation.Evaluator]*) – The evaluator to measure the score.
- **trial** (*Optional[Trial]*) – The current optuna trial under the study (if any.)
- **max_epoch** (*int*) – Maximal number of epochs. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 128.
- **validate_epoch** (*int*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **validate_epoch** – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

Return type
None

classmethod tune(*data*, *evaluator*, *n_trials=20*, *timeout=None*, *data_suggest_function=None*, *parameter_suggest_function=None*, *fixed_params={}*, *random_seed=None*, *prunning_n_startup_trials=10*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*, *logger=None*)

Perform the optimization step. *optuna.Study* object is created inside this function.

Parameters

- **data** (*Optional[Union[csr_matrix, csc_matrix]]*) – The training data. You can also provide tunable parameter dependent training data by providing *data_suggest_function*. In that case, data must be *None*.

- **evaluator** (evaluation.Evaluator) – The validation evaluator that measures the performance of the recommenders.
- **n_trials** (*int*) – The number of expected trials (including pruned ones). Defaults to 20.
- **timeout** (*Optional[int]*) – If set to some value (in seconds), the study will exit after that time period. Note that the running trials is not interrupted, though. Defaults to *None*.
- **data_suggest_function** (*Optional[Callable[[Trial], Union[csr_matrix, csc_matrix]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns training data. Defaults to *None*.
- **parameter_suggest_function** (*Optional[Callable[[Trial], Dict[str, Any]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns *Dict[str, Any]* (i.e., some keyword arguments of the recommender class). If *None*, *cls.default_suggest_parameter* will be used for the parameter suggestion. Defaults to *None*.
- **fixed_params** (*Dict[str, Any]*) – Fixed parameters passed to recommenders during the optimization procedure. This will replace the suggested parameter (either by *cls.default_suggest_parameter* or *parameter_suggest_function*). Defaults to *dict()*.
- **random_seed** (*Optional[int]*) – The random seed to control *optuna.samplers.TPESampler*. Defaults to *None*.
- **prunning_n_startup_trials** (*int*) – *n_startup_trials* argument passed to the constructor of *optuna.pruners.MedianPruner*.
- **max_epoch** (*int*) – The maximal number of epochs for the training. If iterative learning procedure is not available, this parameter will be ignored.
- **validate_epoch** (*int, optional*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int, optional*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5. Defaults to 5.
- **logger** (*Optional[Logger]*) –

Returns

A tuple that consists of

1. A dict containing the best paramaters. This dict can be passed to the recommender as `**kwargs`.
2. A `pandas.DataFrame` that contains the history of optimization.

Return type

Tuple[*Dict*[str, *Any*], *DataFrame*]

irspack.recommenders.get_recommender_class

irspack.recommenders.**get_recommender_class**(*recommender_name*)

Get recommender class from its class name.

Parameters
recommender_name (*str*) – The class name of the recommender.

Returns
The recommender class with its class name being *recommender_name*.

Return type
Type[BaseRecommender]

A LightFM wrapper for BPR matrix factorization (requires a separate installation of lightFM).

BPRFMRecommender	A LightFM wrapper for our interface.

irspack.recommenders.BPRFMRecommender

class irspack.recommenders.**BPRFMRecommender**(*X_train_all*, *n_components=128*, *item_alpha=1e-09*, *user_alpha=1e-09*, *loss='bpr'*, *n_threads=None*, *train_epochs=128*)

Bases: BaseRecommenderWithEarlyStopping, BaseRecommenderWithUserEmbedding, BaseRecommenderWithItemEmbedding

A LightFM wrapper for our interface.

This will create LightFM instance by

```
fm = LightFM(
    no_components=n_components,
    item_alpha=item_alpha,
    user_alpha=user_alpha,
    loss=loss,
)
```

and run `fm.fit_partial(X, num_threads=self.n_threads)` to train through a single epoch.

Parameters

- **X_train_all** (*csr_matrix*) – Input interaction matrix.
- **n_components** (*int*) – The dimension for latent factor. Defaults to 128.
- **item_alpha** (*float*) – The regularization coefficient for item factors. Defaults to 1e-9.
- **user_alpha** (*float*) – The regularization coefficient for user factors. Defaults to 1e-9.
- **loss** (*str*) – Specifies the loss function type of LightFM. Must be one of {“bpr”, “warp”}. Defaults to “bpr”.
- **train_epochs** (*int*) – Number of training epochs. Defaults to 128.
- **n_threads** (*Optional[int]*) – Specifies the number of threads to use for the computation. If None, the environment variable "IRSPACK_NUM_THREADS_DEFAULT" will be looked up, and if the variable is not set, it will be set to `os.cpu_count()`. Defaults to None.

__init__(*X_train_all*, *n_components=128*, *item_alpha=1e-09*, *user_alpha=1e-09*, *loss='bpr'*, *n_threads=None*, *train_epochs=128*)

Parameters

- **X_train_all** (*Union[csr_matrix, csc_matrix]*) –
- **n_components** (*int*) –
- **item_alpha** (*float*) –
- **user_alpha** (*float*) –
- **loss** (*str*) –
- **n_threads** (*Optional[int]*) –
- **train_epochs** (*int*) –

Methods

__init__(X_train_all[, n_components, ...])	
default_suggest_parameter(trial, fixed_params)	
from_config(X_train_all, config)	
get_item_embedding()	Get item embedding vectors.
get_score(index)	Compute the item recommendation score for a subset of users.
get_score_block(begin, end)	Compute the score for a block of the users.
get_score_cold_user(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_cold_user_remove_seen(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_from_item_embedding(user_indices, ...)	
get_score_from_user_embedding(user_embedding)	Compute the item score from user embedding.
get_score_remove_seen(user_indices)	Compute the item score and mask the item in the training set.
get_score_remove_seen_block(begin, end)	Compute the score for a block of the users, and mask the items in the training set.
get_user_embedding()	Get user embedding vectors.
learn()	Learns and returns itself.
learn_with_optimizer(evaluator, trial[, ...])	Learning procedures with early stopping and pruning.
load_state()	
run_epoch()	
save_state()	
start_learning()	
tune(data, evaluator[, n_trials, timeout, ...])	Perform the optimization step.
tune_with_study(study, data, evaluator[, ...])	

Attributes

default_tune_range
fm

X_train_all: sps.csr_matrix

The matrix to feed into recommender.

`get_item_embedding`()

Get item embedding vectors.

Returns
The latent vector representation of items. Its number of rows is equal to the number of the items.

Return type
ndarray

`get_score`(*index*)

Compute the item recommendation score for a subset of users.

Parameters

- **user_indices** – The index defines the subset of users.
- **index** (*ndarray*) –

Returns
The item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

`get_score_block`(*begin*, *end*)

Compute the score for a block of the users.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`get_score_cold_user`(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_cold_user_remove_seen`(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix. The score will then be masked by the input.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed & masked item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_from_user_embedding`(*user_embedding*)

Compute the item score from user embedding. Mainly used for cold-start scenario.

Parameters
user_embedding (*ndarray*) – Latent user representation obtained elsewhere.

Returns
The score array. Its shape will be `(user_embedding.shape[0], self.n_items)`

Return type
DenseScoreArray

`get_score_remove_seen`(*user_indices*)

Compute the item score and mask the item in the training set. Masked items will have the score -inf.

Parameters
user_indices (*ndarray*) – Specifies the subset of users.

Returns
The masked item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

`get_score_remove_seen_block`(*begin*, *end*)

Compute the score for a block of the users, and mask the items in the training set. Masked items will have the score -inf.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The masked item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`get_user_embedding`()

Get user embedding vectors.

Returns
The latent vector representation of users. Its number of rows is equal to the number of the users.

Return type
ndarray

`learn`()

Learns and returns itself.

Returns
The model after fitting process.

Parameters
self (*R*) –

Return type
R

learn_with_optimizer(*evaluator*, *trial*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*)

Learning procedures with early stopping and pruning.

Parameters

- **evaluator** (*Optional[evaluation.Evaluator]*) – The evaluator to measure the score.
- **trial** (*Optional[Trial]*) – The current optuna trial under the study (if any.)
- **max_epoch** (*int*) – Maximal number of epochs. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 128.
- **validate_epoch** (*int*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **validate_epoch** – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

Return type
None

classmethod **tune**(*data*, *evaluator*, *n_trials=20*, *timeout=None*, *data_suggest_function=None*, *parameter_suggest_function=None*, *fixed_params={}*, *random_seed=None*, *prunning_n_startup_trials=10*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*, *logger=None*)

Perform the optimization step. *optuna.Study* object is created inside this function.

Parameters

- **data** (*Optional[Union[csr_matrix, csc_matrix]]*) – The training data. You can also provide tunable parameter dependent training data by providing *data_suggest_function*. In that case, data must be *None*.
- **evaluator** (*evaluation.Evaluator*) – The validation evaluator that measures the performance of the recommenders.
- **n_trials** (*int*) – The number of expected trials (including pruned ones). Defaults to 20.
- **timeout** (*Optional[int]*) – If set to some value (in seconds), the study will exit after that time period. Note that the running trials is not interrupted, though. Defaults to *None*.
- **data_suggest_function** (*Optional[Callable[[Trial], Union[csr_matrix, csc_matrix]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns training data. Defaults to *None*.
- **parameter_suggest_function** (*Optional[Callable[[Trial], Dict[str, Any]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns *Dict[str, Any]* (i.e., some keyword arguments of the recommender class). If *None*, *cls.default_suggest_parameter* will be used for the parameter suggestion. Defaults to *None*.

- **fixed_params** (*Dict[str, Any]*) – Fixed parameters passed to recommenders during the optimization procedure. This will replace the suggested parameter (either by *cls.default_suggest_parameter* or *parameter_suggest_function*). Defaults to *dict()*.
- **random_seed** (*Optional[int]*) – The random seed to control *optuna.samplers.TPESampler*. Defaults to *None*.
- **prunning_n_startup_trials** (*int*) – *n_startup_trials* argument passed to the constructor of *optuna.pruners.MedianPruner*.
- **max_epoch** (*int*) – The maximal number of epochs for the training. If iterative learning procedure is not available, this parameter will be ignored.
- **validate_epoch** (*int, optional*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int, optional*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5. Defaults to 5.
- **logger** (*Optional[Logger]*) –

Returns

A tuple that consists of

1. A dict containing the best paramaters. This dict can be passed to the recommender as `**kwargs`.
2. A `pandas.DataFrame` that contains the history of optimization.

Return type
Tuple[*Dict*[str, *Any*], *DataFrame*]

As a reference code based on neural networks, we have implemented a JAX version of Mult-VAE, which requires `jax`, `jaxlib`, `dm-haiku`, and `optax`:

MultVAERecommender	JAX implementation of Mult-VAE, presented in "Variational Autoencoders for Collaborative Filtering".

irspack.recommenders.MultVAERecommender

class irspack.recommenders.**MultVAERecommender**(*X_train_all*, *dim_z=16*, *enc_hidden_dims=256*, *dec_hidden_dims=None*, *dropout_p=0.5*, *l2_regularizer=0*, *kl_anneal_goal=0.2*, *anneal_end_epoch=50*, *minibatch_size=512*, *train_epochs=300*, *learning_rate=0.001*)

Bases: `BaseRecommenderWithEarlyStopping`

JAX implementation of Mult-VAE, presented in "Variational Autoencoders for Collaborative Filtering".

Parameters

- **X_train_all** (*csr_matrix*) – The source data.
- **dim_z** (*int*) – The latend dimension.
- **enc_hidden_dims** (*int*) – The encoder's intermediate layer dimension.

- **dec_hidden_dims** (*Optional[int]*) – The dimensions of the decoder's intermediate layers.
- **dropout_p** (*float*) – Dropout ratio. Defaults to 0.5.
- **l2_regularizer** (*float*) – L2 regularization coefficient. Defaults to 0.
- **kl_anneal_goal** (*float*) – beta of beta-VAE. Defaults to 0.2.
- **anneal_end_epoch** (*int*) – The epoch to complete the annealing.. Defaults to 50.
- **minibatch_size** (*int, optional*) – Minibatch size. Defaults to 512.
- **train_epochs** (*int*) – The number of epochs to run. Defaults to 300.
- **learning_rate** (*float*) – Adam optimizer's learning rate. Defaults to 1e-3.

__init__(*X_train_all*, *dim_z=16*, *enc_hidden_dims=256*, *dec_hidden_dims=None*, *dropout_p=0.5*, *l2_regularizer=0*, *kl_anneal_goal=0.2*, *anneal_end_epoch=50*, *minibatch_size=512*, *train_epochs=300*, *learning_rate=0.001*)

Parameters

- **X_train_all** (*Union[csr_matrix, csc_matrix]*) –
- **dim_z** (*int*) –
- **enc_hidden_dims** (*int*) –
- **dec_hidden_dims** (*Optional[int]*) –
- **dropout_p** (*float*) –
- **l2_regularizer** (*float*) –
- **kl_anneal_goal** (*float*) –
- **anneal_end_epoch** (*int*) –
- **minibatch_size** (*int*) –
- **train_epochs** (*int*) –
- **learning_rate** (*float*) –

Return type
None

Methods

__init__(X_train_all[, dim_z, ...])	
default_suggest_parameter(trial, fixed_params)	
from_config(X_train_all, config)	
get_score(user_indices)	Compute the item recommendation score for a subset of users.
get_score_block(begin, end)	Compute the score for a block of the users.
get_score_cold_user(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_cold_user_remove_seen(X)	Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.
get_score_remove_seen(user_indices)	Compute the item score and mask the item in the training set.
get_score_remove_seen_block(begin, end)	Compute the score for a block of the users, and mask the items in the training set.
learn()	Learns and returns itself.
learn_with_optimizer(evaluator, trial[, ...])	Learning procedures with early stopping and pruning.
load_state()	
run_epoch()	
save_state()	
start_learning()	
tune(data, evaluator[, n_trials, timeout, ...])	Perform the optimization step.
tune_with_study(study, data, evaluator[, ...])	

Attributes

default_tune_range

X_train_all: sps.csr_matrix

The matrix to feed into recommender.

get_score(*user_indices*)

Compute the item recommendation score for a subset of users.

Parameters

user_indices (*ndarray*) – The index defines the subset of users.

Returns

The item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

`get_score_block`(*begin*, *end*)

Compute the score for a block of the users.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

`get_score_cold_user`(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_cold_user_remove_seen`(*X*)

Compute the item recommendation score for unseen users whose profiles are given as another user-item relation matrix. The score will then be masked by the input.

Parameters
X (*Union[csr_matrix, csc_matrix]*) – The profile user-item relation matrix for unseen users. Its number of rows is arbitrary, but the number of columns must be self.n_items.

Returns
Computed & masked item scores for users. Its shape is equal to X.

Return type
ndarray

`get_score_remove_seen`(*user_indices*)

Compute the item score and mask the item in the training set. Masked items will have the score -inf.

Parameters
user_indices (*ndarray*) – Specifies the subset of users.

Returns
The masked item scores. Its shape will be (len(user_indices), self.n_items)

Return type
ndarray

`get_score_remove_seen_block`(*begin*, *end*)

Compute the score for a block of the users, and mask the items in the training set. Masked items will have the score -inf.

Parameters

- **begin** (*int*) – where the evaluated user block begins.
- **end** (*int*) – where the evaluated user block ends.

Returns
The masked item scores. Its shape will be (end - begin, self.n_items)

Return type
ndarray

learn()

Learns and returns itself.

Returns
The model after fitting process.

Parameters
self (*R*) –

Return type
R

learn_with_optimizer(*evaluator*, *trial*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*)

Learning procedures with early stopping and pruning.

Parameters

- **evaluator** (*Optional[evaluation.Evaluator]*) – The evaluator to measure the score.
- **trial** (*Optional[Trial]*) – The current optuna trial under the study (if any.)
- **max_epoch** (*int*) – Maximal number of epochs. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 128.
- **validate_epoch** (*int*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **validate_epoch** – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.

Return type
None

classmethod tune(*data*, *evaluator*, *n_trials=20*, *timeout=None*, *data_suggest_function=None*, *parameter_suggest_function=None*, *fixed_params={}*, *random_seed=None*, *prunning_n_startup_trials=10*, *max_epoch=128*, *validate_epoch=5*, *score_degradation_max=5*, *logger=None*)

Perform the optimization step. *optuna.Study* object is created inside this function.

Parameters

- **data** (*Optional[Union[csr_matrix, csc_matrix]]*) – The training data. You can also provide tunable parameter dependent training data by providing *data_suggest_function*. In that case, data must be *None*.
- **evaluator** (*evaluation.Evaluator*) – The validation evaluator that measures the performance of the recommenders.
- **n_trials** (*int*) – The number of expected trials (including pruned ones). Defaults to 20.

- **timeout** (*Optional[int]*) – If set to some value (in seconds), the study will exit after that time period. Note that the running trials is not interrupted, though. Defaults to *None*.
- **data_suggest_function** (*Optional[Callable[[Trial], Union[csr_matrix, csc_matrix]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns training data. Defaults to *None*.
- **parameter_suggest_function** (*Optional[Callable[[Trial], Dict[str, Any]]]*) – If not *None*, this must be a function which takes *optuna.Trial* as its argument and returns *Dict[str, Any]* (i.e., some keyword arguments of the recommender class). If *None*, *cls.default_suggest_parameter* will be used for the parameter suggestion. Defaults to *None*.
- **fixed_params** (*Dict[str, Any]*) – Fixed parameters passed to recommenders during the optimization procedure. This will replace the suggested parameter (either by *cls.default_suggest_parameter* or *parameter_suggest_function*). Defaults to *dict()*.
- **random_seed** (*Optional[int]*) – The random seed to control *optuna.samplers.TPESampler*. Defaults to *None*.
- **prunning_n_startup_trials** (*int*) – *n_startup_trials* argument passed to the constructor of *optuna.pruners.MedianPruner*.
- **max_epoch** (*int*) – The maximal number of epochs for the training. If iterative learning procedure is not available, this parameter will be ignored.
- **validate_epoch** (*int, optional*) – The frequency of validation score measurement. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5.
- **score_degradation_max** (*int, optional*) – Maximal number of allowed score degradation. If iterative learning procedure is not available, this parameter will be ignored. Defaults to 5. Defaults to 5.
- **logger** (*Optional[Logger]*) –

Returns

A tuple that consists of

1. A dict containing the best paramaters. This dict can be passed to the recommender as `**kwargs`.
2. A `pandas.DataFrame` that contains the history of optimization.

Return type

Tuple[*Dict*[str, *Any*], *DataFrame*]

1.4.3 Split Functions

UserTrainTestInteractionPair	A class to hold users' train & test (if any) interactions and their ids.
rowwise_train_test_split	Splits the non-zero elements of a sparse matrix into two (train & test interactions).
split_dataframe_partial_user_holdout	Splits the DataFrame and build an interaction matrix, holding out random interactions for a subset of randomly selected users (whom we call "validation users" and "test users").
holdout_specific_interactions	Holds-out (part of) the interactions specified by the users.
split_last_n_interaction_df	Split a dataframe holding out last *n_heldout* or last *held-out_ratio* part of interactions of the users.

irspack.split.UserTrainTestInteractionPair

class irspack.split.**UserTrainTestInteractionPair**(*user_ids*, *X_train*, *X_test*, *item_ids=None*)

Bases: `object`

A class to hold users' train & test (if any) interactions and their ids.

Parameters

- **user_ids** (*Union[List[Any], ndarray]*) – List of user ids. Its `i`-th element should correspond to `i`-th row of `X_train`.
- **X_train** (*csr_matrix*) – The train part of interactions.
- **X_test** (*csr_matrix*) – The test part of interactions (if any). If `None`, an empty matrix with the shape of `X_train` will be created. Defaults to None.
- **item_ids** (*Optional[Union[List[Any], ndarray]]*) –

Raises

- **ValueError** – when `X_train` and `user_ids` have inconsistent size.
- **ValueError** – when `X_train` and `X_test` have inconsistent size.

__init__(*user_ids*, *X_train*, *X_test*, *item_ids=None*)

Parameters

- **user_ids** (*Union[List[Any], ndarray]*) –
- **X_train** (*Union[csr_matrix, csc_matrix]*) –
- **X_test** (*Optional[Union[csr_matrix, csc_matrix]]*) –
- **item_ids** (*Optional[Union[List[Any], ndarray]]*) –

Methods

__init__(user_ids, X_train, X_test[, item_ids])	

concat(other)	Concatenate the users data.
df_test()	
df_train()	

Attributes

X_train	The train part of users' interactions.
X_test	The test part of users' interactions.
n_users	The number of users
n_items	The number of items
X_all	If X_test is not None, equal to X_train + X_test.Otherwise equals X_train.

X_all: csr_matrix

If X_test is not None, equal to X_train + X_test.Otherwise equals X_train.

X_test: csr_matrix

The test part of users' interactions.

X_train: csr_matrix

The train part of users' interactions.

concat(*other*)

Concatenate the users data. user_id will be self.user_ids + self.item_ids.

Returns
[description]

Return type
[type]

Parameters
other (UserTrainTestInteractionPair) –

ValueError:
when self and other have unequal n_items.

n_items: int

The number of items

n_users: int

The number of users

irspack.split.rowwise_train_test_split

irspack.split.**rowwise_train_test_split**(*X*, *test_ratio=0.5*, *n_test=None*, *ceil_n_heldout=False*, *random_state=None*)

Splits the non-zero elements of a sparse matrix into two (train & test interactions). For each row, the ratio of non-zero elements that become the test interaction is (approximately) constant.

Parameters

- **X** (*Union[csr_matrix, csc_matrix]*) – The source sparse matrix.
- **test_ratio** (*float*) – The ratio of test interactions for each row. That is, for each row, if it contains NNZ-nonzero elements, the number of elements entering into the test interaction will be `math.floor(test_ratio * NNZ)`. Defaults to 0.5.
- **random_state** (*Union[None, int, RandomState]*) – The random state. Defaults to *None*.
- **n_test** (*Optional[int]*) –
- **ceil_n_heldout** (*bool*) –

Returns
A tuple of train & test interactions, which sum back to the original matrix.

Return type
Tuple[*Union*[*csr_matrix*, *csc_matrix*], *Union*[*csr_matrix*, *csc_matrix*]]

irspack.split.split_dataframe_partial_user_holdout

irspack.split.**split_dataframe_partial_user_holdout**(*df_all*, *user_column*, *item_column*, *time_column=None*, *rating_column=None*, *n_val_user=None*, *n_test_user=None*, *val_user_ratio=0.1*, *test_user_ratio=0.1*, *heldout_ratio_val=0.5*, *n_heldout_val=None*, *heldout_ratio_test=0.5*, *n_heldout_test=None*, *ceil_n_heldout=False*, *random_state=None*)

Splits the DataFrame and build an interaction matrix, holding out random interactions for a subset of randomly selected users (whom we call "validation users" and "test users").

Parameters

- **df_all** (*DataFrame*) – The user-item interaction event log.
- **user_column** (*str*) – The column name for user_id.
- **item_column** (*str*) – The column name for movie_id.
- **time_column** (*Optional[str]*) – The column name (if any) specifying the time of the interaction. If this is set, the split will be based on time, and some of the most recent interactions will be held out for each user. Defaults to None.
- **rating_column** (*Optional[str]*) – The column name for ratings. If None, the rating will be treated as 1 for all interactions. Defaults to None.
- **n_val_user** (*Optional[int]*) – The number of "validation users". Defaults to None.
- **n_test_user** (*Optional[int]*) – The number of "test users". Defaults to None.
- **val_user_ratio** (*float*) – The percentage of "validation users" with respect to all users. Ignored when `n_val_user` is set. Defaults to 0.1.

- **test_user_ratio** (*float*) – The percentage of "test users" with respect to all users. Ignored when `n_text_user` is set. Defaults to 0.1.
- **heldout_ratio_val** (*float*) – The percentage of held-out interactions for "validation users". Ignored if `n_heldout_val` is specified. Defaults to 0.5.
- **n_heldout_val** (*Optional[int]*) – The maximal number of held-out interactions for "validation users".
- **heldout_ratio_test** (*float*) – The percentage of held-out interactions for "test users". Ignored if `n_heldout_test` is specified. Defaults to 0.5.
- **n_heldout_val** – The maximal number of held-out interactions for "test users".
- **ceil_n_heldout** (*bool*) – If *True*, the number of held-out interactions of user *u* will be *ceil(heldout_ratio_val * N_u)* and *ceil(heldout_ratio_test * N_u)*. If *False*, *floor* function will be used instead. Defaults to *False*.
- **random_state** (*Union[None, int, RandomState]*) – The random state for this procedure. Defaults to *None*.
- **n_heldout_test** (*Optional[int]*) –

Raises

ValueError – When `n_val_user + n_test_user` is greater than the number of total users.

Returns

1. A dictionary with `"train"`, `"val"`, `"test"` as its keys and the coressponding dataset as its values.
2. List of unique item ids (which corresponds to the columns of the datasets).

Return type

A tuple consisting of

irspack.split.holdout_specific_interactions

irspack.split.**holdout_specific_interactions**(*df*, *user_column*, *item_column*, *interaction_indicator*, *validatable_user_ratio_val=0.2*, *validatable_user_ratio_test=0.2*, *random_state=None*)

Holds-out (part of) the interactions specified by the users.

All the users will be split into two category:

1. Those who have an interaction in the specified subset. We denote them as "validatable" users.
2. Those who don't.

We split the users in 1. into three parts (train, validation, test)-users, and hold-out the specified interactions. The interactions of non-validatable users will be part of the train dataset.

This split will be useful when want to:

- recommend only part of the items (e.g., rather unpopular ones) to the users. In this case, the held-out interactions will be the ones with these specific items.
- split the dataframe by a certain timepoint, and ensure that no information after that timepoint contaminates the training set.

Parameters

- **df** (*DataFrame*) – The data source.

- **user_column** (*str*) – The column name of the users.
- **item_column** (*str*) – The column name of the items.
- **interaction_indicator** (*ndarray*) – Specifies where in `df` the held-out interactions are.
- **validatable_user_ratio_val** (*float*) – The ratio of "validation-set users" in the "validatable users". Defaults to 0.2.
- **validatable_user_ration_test** – The ratio of "test-set users" in the "validatable users". Defaults to 0.2.
- **random_state** (*Union[None, int, RandomState]*) – The random seed used to split validatable users into three. Defaults to *None*.
- **validatable_user_ratio_test** (*float*) –

Returns

A tuple consiting of

- The aligned list of all the items.
- A dictionary with train/val/test user pairs.

Return type
Tuple[*List*[*Any*], *Dict*[str, UserTrainTestInteractionPair]]

irspack.split.split_last_n_interaction_df

irspack.split.**split_last_n_interaction_df**(*df*, *user_column*, *timestamp_column*, *n_heldout=None*, *heldout_ratio=0.1*, *ceil_n_heldout=False*)

Split a dataframe holding out last *n_heldout* or last *heldout_ratio* part of interactions of the users.

Parameters

- **df** (*DataFrame*) – The Dataframe to be split.
- **user_column** (*str*) – The column name for users.
- **timestamp_column** (*str*) – The column name for "timestamp" (it doesn't have to be datetime).
- **n_heldout** (*Optional[int]*) – If not *None*, specifies the maximal number of last actions to be held-out. Defaults to None.
- **heldout_ratio** (*float*) – Specifies how much of each user interaction will be held out. Ignored if `n_heldout` is present.
- **ceil_n_heldout** (*bool*) – If this is *True* and *n_heldout* is *None*, the number of test interaction for a given user *u* will be *ceil(N_u * heldout_ratio)* where *N_u* is the number of interactions fo *u*. If this is *False*, *floor(N_u * heldout_ratio)* will be used instead. Defaults to *False*.

Returns
First interactions and held-out interactions.

Return type
Tuple[*DataFrame*, *DataFrame*]

1.4.4 Utilities

ItemIDMapper	A utility class that helps mapping item IDs to indices or vice versa.
IDMapper	A utility class that helps mapping user/item IDs to indices or vice versa.

irspack.utils.ItemIDMapper

class irspack.utils.**ItemIDMapper**(*item_ids*)

Bases: Generic[ItemIdType]

A utility class that helps mapping item IDs to indices or vice versa.

Parameters
item_ids – List of item IDs. The ordering of this list should be consistent with the item indices of recommenders or score arrays to be used.

Raises
ValueError – When there is a duplicate in item_ids.

__init__(*item_ids*)

Parameters
item_ids (*List[ItemIdType]*) –

Methods

__init__(item_ids)	
list_of_user_profile_to_matrix(users_info)	Converts users' profiles (interaction histories for the users) into a sparse matrix.
recommend_for_new_user(recommender, user_profile)	Retrieves recommendations for an unknown user by using the user's contact history with the known items. :param recommender: The recommender for scoring. :param user_profile: User's profile given either as a list of item ids the user had a cotact or a item id-rating dict. Previously unseen item ID will be ignored. :param cutoff: Maximal number of recommendations allowed. :param allowed_item_ids: If not None, recommend the items within this list. If None, all known item ids can be recommended (except for those in item_ids argument). Defaults to None. :param forbidden_item_ids: If not None, never recommend the items within the list. Defaults to None.
recommend_for_new_user_batch(recommender, ...)	Retrieves recommendations for unknown users by using their contact history with the known items.
score_to_recommended_items(score, cutoff[, ...])	
score_to_recommended_items_batch(score, cutoff)	Retrieve recommendation from score array.

list_of_user_profile_to_matrix(*users_info*)

Converts users' profiles (interaction histories for the users) into a sparse matrix.

Parameters

users_info (*Sequence[Union[List[ItemIdType], Dict[ItemIdType, float]]]*) – A list of user profiles. Each profile should be either the item ids that the user cotacted or a dictionary of item ratings. Previously unseen item IDs will be ignored.

Returns

The converted sparse matrix. Each column correspond to *self.items_ids*.

Return type

csr_matrix

recommend_for_new_user(*recommender*, *user_profile*, *cutoff=20*, *allowed_item_ids=None*, *forbidden_item_ids=None*)

Retrieves recommendations for an unknown user by using the user's contact history with the known items. :param recommender: The recommender for scoring. :param user_profile: User's profile given either as a list of item ids the user had a cotact or a item id-rating dict.

Previously unseen item ID will be ignored.

Parameters

- **cutoff** (*int*) – Maximal number of recommendations allowed.
- **allowed_item_ids** (*Optional[List[ItemIdType]]*) – If not `None`, recommend the items within this list. If `None`, all known item ids can be recommended (except for those in `item_ids` argument). Defaults to `None`.
- **forbidden_item_ids** (*Optional[List[ItemIdType]]*) – If not `None`, never recommend the items within the list. Defaults to None.
- **recommender** (`BaseRecommender`) –
- **user_profile** (*Union[List[ItemIdType], Dict[ItemIdType, float]]*) –

Returns

A List of tuples consisting of `(item_id, score)`.

Return type

List[*Tuple*[*ItemIdType*, float]]

recommend_for_new_user_batch(*recommender*, *user_profiles*, *cutoff=20*, *allowed_item_ids=None*, *per_user_allowed_item_ids=None*, *forbidden_item_ids=None*, *n_threads=None*)

Retrieves recommendations for unknown users by using their contact history with the known items.

Parameters

- **recommender** (`BaseRecommender`) – The recommender for scoring.
- **user_profiles** (*Sequence[Union[List[ItemIdType], Dict[ItemIdType, float]]]*) – A list of user profiles. Each profile should be either the item ids the user had a cotact, or item-rating dict. Previously unseen item IDs will be ignored.
- **cutoff** (*int*) – Maximal number of recommendations allowed.
- **allowed_item_ids** (*Optional[List[ItemIdType]]*) – If not `None`, defines "a list of recommendable item IDs". Ignored if *per_user_allowed_item_ids* is set.

- **per_user_allowed_item_ids** (*Optional[List[List[ItemIdType]]]*) – If not None, defines "a list of list of recommendable item IDs" and `len(allowed_item_ids)` must be equal to `score.shape[0]`. Defaults to None.
- **forbidden_item_ids** (*Optional[List[List[ItemIdType]]]*) – If not None, defines "a list of list of forbidden item IDs" and `len(allowed_item_ids)` must be equal to `len(item_ids)` Defaults to None.
- **n_threads** (*Optional[int]*) – Specifies the number of threads to use for the computation. If None, the environment variable `"IRSPACK_NUM_THREADS_DEFAULT"` will be looked up, and if the variable is not set, it will be set to `os.cpu_count()`. Defaults to None.

Returns
A list of list of tuples consisting of `(item_id, score)`. Each internal list corresponds to the recommender's recommendation output.

Return type
List[*List*[*Tuple*[*ItemIdType*, float]]]

score_to_recommended_items_batch(*score*, *cutoff*, *allowed_item_ids=None*, *per_user_allowed_item_ids=None*, *forbidden_item_ids=None*, *n_threads=None*)

Retrieve recommendation from score array. An item with negative infinity score for a user will not be recommended for the user.

Parameters

- **score** (*ndarray*) – 1d numpy ndarray for score.
- **cutoff** (*int*) – Maximal number of recommendations allowed.
- **allowed_item_ids** (*Optional[List[ItemIdType]]*) – If not None, defines "a list of recommendable item IDs". Ignored if *per_user_allowed_item_ids* is set.
- **per_user_allowed_item_ids** (*Optional[List[List[ItemIdType]]]*) – If not None, defines "a list of list of recommendable item IDs" and `len(allowed_item_ids)` must be equal to `score.shape[0]`. Defaults to None.
- **allowed_item_ids** – If not None, defines "a list of list of recommendable item IDs" and `len(allowed_item_ids)` must be equal to `len(item_ids)`. Defaults to None.
- **forbidden_item_ids** (*Optional[List[List[ItemIdType]]]*) – If not None, defines "a list of list of forbidden item IDs" and `len(allowed_item_ids)` must be equal to `len(item_ids)` Defaults to None.
- **n_threads** (*Optional[int]*) –

Return type
List[*List*[*Tuple*[*ItemIdType*, float]]]

irspack.utils.IDMapper

class irspack.utils.**IDMapper**(*user_ids*, *item_ids*)

Bases: Generic[UserIdType, ItemIdType], *ItemIDMapper*[ItemIdType]

A utility class that helps mapping user/item IDs to indices or vice versa.

Parameters

- **user_ids** – List of user IDs. The ordering should be consistent with the user indices of recommenders to be used.
- **item_ids** – List of item IDs. The ordering should be consistent with the item indices of recommenders or score arrays to be used.

Raises

ValueError – When there is a duplicate in item_ids.

__init__(*user_ids*, *item_ids*)

Parameters

- **user_ids** (*List[UserIdType]*) –
- **item_ids** (*List[ItemIdType]*) –

Methods

__init__(user_ids, item_ids)	
list_of_user_profile_to_matrix(users_info)	Converts users' profiles (interaction histories for the users) into a sparse matrix.
recommend_for_known_user_batch(recommender, ...)	Retrieves recommendation for known users.
recommend_for_known_user_id(recommender, user_id)	Retrieve recommendation result for a known user. :param recommender: The recommender for scoring. :param user_id: The target user ID. :param cutoff: Maximal number of recommendations allowed. :param allowed_item_ids: If not `None`, recommend the items within this list. If `None`, all known item ids can be recommended (except for those in `item_ids` argument). Defaults to `None`. :param forbidden_item_ids: If not `None`, never recommend the items within the list. Defaults to None.
recommend_for_new_user(recommender, user_profile)	Retrieves recommendations for an unknown user by using the user's contact history with the known items. :param recommender: The recommender for scoring. :param user_profile: User's profile given either as a list of item ids the user had a cotact or a item id-rating dict. Previously unseen item ID will be ignored. :param cutoff: Maximal number of recommendations allowed. :param allowed_item_ids: If not `None`, recommend the items within this list. If `None`, all known item ids can be recommended (except for those in `item_ids` argument). Defaults to `None`. :param forbidden_item_ids: If not `None`, never recommend the items within the list. Defaults to None.
recommend_for_new_user_batch(recommender, ...)	Retrieves recommendations for unknown users by using their contact history with the known items.
`score_to_recommended_items`(score, cutoff[, ...])	
score_to_recommended_items_batch(score, cutoff)	Retrieve recommendation from score array.

list_of_user_profile_to_matrix(*users_info*)

Converts users' profiles (interaction histories for the users) into a sparse matrix.

Parameters

users_info (*Sequence[Union[List[ItemIdType], Dict[ItemIdType, float]]]*) – A list of user profiles. Each profile should be either the item ids that the user cotacted or a dictionary of item ratings. Previously unseen item IDs will be ignored.

Returns

The converted sparse matrix. Each column correspond to *self.items_ids*.

Return type

csr_matrix

recommend_for_known_user_batch(*recommender*, *user_ids*, *cutoff=20*, *allowed_item_ids=None*, *per_user_allowed_item_ids=None*, *forbidden_item_ids=None*, *n_threads=None*)

Retrieves recommendation for known users.

Parameters

- **recommender** (BaseRecommender) – The recommender for scoring.
- **user_ids** (*List[UserIdType]*) – A list of user ids.
- **cutoff** (*int*) – Maximal number of recommendations allowed.
- **allowed_item_ids** (*Optional[List[ItemIdType]]*) – If not `None`, defines "a list of recommendable item IDs". Ignored if *per_user_allowed_item_ids* is set.
- **per_user_allowed_item_ids** (*Optional[List[List[ItemIdType]]]*) – If not `None`, defines "a list of list of recommendable item IDs" and `len(allowed_item_ids)` must be equal to `score.shape[0]`. Defaults to `None`.
- **forbidden_item_ids** (*Optional[List[List[ItemIdType]]]*) – If not `None`, defines "a list of list of forbidden item IDs" and `len(allowed_item_ids)` must be equal to `len(item_ids)` Defaults to `None`.
- **n_threads** (*Optional[int]*) – Specifies the number of threads to use for the computation. If `None`, the environment variable `"IRSPACK_NUM_THREADS_DEFAULT"` will be looked up, and if the variable is not set, it will be set to `os.cpu_count()`. Defaults to None.

Returns

A list of list of tuples consisting of `(item_id, score)`. Each internal list corresponds to the recommender's recommendation output.

Return type

List[*List*[*Tuple*[*ItemIdType*, float]]]

recommend_for_known_user_id(*recommender*, *user_id*, *cutoff=20*, *allowed_item_ids=None*, *forbidden_item_ids=None*)

Retrieve recommendation result for a known user. :param recommender: The recommender for scoring. :param user_id: The target user ID. :param cutoff: Maximal number of recommendations allowed. :param allowed_item_ids: If not `None`, recommend the items within this list.

If `None`, all known item ids can be recommended (except for those in `item_ids` argument). Defaults to `None`.

Parameters

- **forbidden_item_ids** (*Optional[List[ItemIdType]]*) – If not `None`, never recommend the items within the list. Defaults to None.
- **recommender** (BaseRecommender) –
- **user_id** (*UserIdType*) –
- **cutoff** (*int*) –
- **allowed_item_ids** (*Optional[List[ItemIdType]]*) –

Raises

RuntimeError – When user_id is not in `self.user_ids`.

Returns

A List of tuples consisting of `(item_id, score)`.

Return type

List[*Tuple*[*ItemIdType*, float]]

recommend_for_new_user(*recommender*, *user_profile*, *cutoff=20*, *allowed_item_ids=None*, *forbidden_item_ids=None*)

Retrieves recommendations for an unknown user by using the user's contact history with the known items. :param recommender: The recommender for scoring. :param user_profile: User's profile given either as a list of item ids the user had a cotact or a item id-rating dict.

Previously unseen item ID will be ignored.

Parameters

- **cutoff** (*int*) – Maximal number of recommendations allowed.
- **allowed_item_ids** (*Optional[List[ItemIdType]]*) – If not `None`, recommend the items within this list. If `None`, all known item ids can be recommended (except for those in `item_ids` argument). Defaults to `None`.
- **forbidden_item_ids** (*Optional[List[ItemIdType]]*) – If not `None`, never recommend the items within the list. Defaults to None.
- **recommender** (BaseRecommender) –
- **user_profile** (*Union[List[ItemIdType], Dict[ItemIdType, float]]*) –

Returns
A List of tuples consisting of `(item_id, score)`.

Return type
List[*Tuple*[*ItemIdType*, float]]

recommend_for_new_user_batch(*recommender*, *user_profiles*, *cutoff=20*, *allowed_item_ids=None*, *per_user_allowed_item_ids=None*, *forbidden_item_ids=None*, *n_threads=None*)

Retrieves recommendations for unknown users by using their contact history with the known items.

Parameters

- **recommender** (BaseRecommender) – The recommender for scoring.
- **user_profiles** (*Sequence[Union[List[ItemIdType], Dict[ItemIdType, float]]]*) – A list of user profiles. Each profile should be either the item ids the user had a cotact, or item-rating dict. Previously unseen item IDs will be ignored.
- **cutoff** (*int*) – Maximal number of recommendations allowed.
- **allowed_item_ids** (*Optional[List[ItemIdType]]*) – If not `None`, defines "a list of recommendable item IDs". Ignored if *per_user_allowed_item_ids* is set.
- **per_user_allowed_item_ids** (*Optional[List[List[ItemIdType]]]*) – If not `None`, defines "a list of list of recommendable item IDs" and `len(allowed_item_ids)` must be equal to `score.shape[0]`. Defaults to `None`.
- **forbidden_item_ids** (*Optional[List[List[ItemIdType]]]*) – If not `None`, defines "a list of list of forbidden item IDs" and `len(allowed_item_ids)` must be equal to `len(item_ids)` Defaults to `None`.
- **n_threads** (*Optional[int]*) – Specifies the number of threads to use for the computation. If `None`, the environment variable `"IRSPACK_NUM_THREADS_DEFAULT"` will be looked up, and if the variable is not set, it will be set to `os.cpu_count()`. Defaults to None.

Returns
A list of list of tuples consisting of `(item_id, score)`. Each internal list corresponds to the recommender's recommendation output.

Return type
List[*List*[*Tuple*[*ItemIdType*, float]]]

`score_to_recommended_items_batch`(*score*, *cutoff*, *allowed_item_ids=None*, *per_user_allowed_item_ids=None*, *forbidden_item_ids=None*, *n_threads=None*)

Retrieve recommendation from score array. An item with negative infinity score for a user will not be recommended for the user.

Parameters

- **score** (*ndarray*) – 1d numpy ndarray for score.
- **cutoff** (*int*) – Maximal number of recommendations allowed.
- **allowed_item_ids** (*Optional[List[ItemIdType]]*) – If not `None`, defines "a list of recommendable item IDs". Ignored if *per_user_allowed_item_ids* is set.
- **per_user_allowed_item_ids** (*Optional[List[List[ItemIdType]]]*) – If not `None`, defines "a list of list of recommendable item IDs" and `len(allowed_item_ids)` must be equal to `score.shape[0]`. Defaults to `None`.
- **allowed_item_ids** – If not `None`, defines "a list of list of recommendable item IDs" and `len(allowed_item_ids)` must be equal to `len(item_ids)`. Defaults to `None`.
- **forbidden_item_ids** (*Optional[List[List[ItemIdType]]]*) – If not `None`, defines "a list of list of forbidden item IDs" and `len(allowed_item_ids)` must be equal to `len(item_ids)` Defaults to `None`.
- **n_threads** (*Optional[int]*) –

Return type
List[*List*[*Tuple*[*ItemIdType*, float]]]

1.4.5 Dataset

MovieLens1MDataManager	Manages MovieLens 1M dataset.
MovieLens100KDataManager	Manages MovieLens 100K dataset.
MovieLens20MDataManager	
NeuMFML1MDownloader	Manages MovieLens 1M dataset split under 1-vs-100 negative evaluation protocol.

irspack.dataset.MovieLens1MDataManager

class irspack.dataset.**MovieLens1MDataManager**(*zippath=None*, *force_download=False*)

Bases: BaseMovieLenstDataLoader

Manages MovieLens 1M dataset.

Parameters

- **zippath** (*Optional[Union[Path, str]]*) – Where the zipped data is located. If *None*, assumes the path to be *~/.ml-1m.zip*. If the designated path does not exist, you will be prompted for the permission to download the data. Defaults to *None*.
- **force_download** (*bool*) – If *True*, the class will not prompt for the permission and start downloading immediately.

__init__(*zippath=None*, *force_download=False*)

Specify the zip path for dataset. If that path does not exist, try downloading the relevant data from online resources.

Parameters

- **zippath** (*Optional[Union[Path, str]], optional*) – _description_. Defaults to None.
- **force_download** (*bool, optional*) – _description_. Defaults to False.

Raises

RuntimeError – _description_

Methods

__init__([zippath, force_download])	Specify the zip path for dataset.
read_interaction()	Reads the entire user/movie/rating/timestamp interaction data.
read_item_info()	
read_user_info()	

Attributes

DEFAULT_PATH
DOWNLOAD_URL
INTERACTION_PATH
ITEM_INFO_PATH
USER_INFO_PATH

read_interaction()

Reads the entire user/movie/rating/timestamp interaction data.

Returns

The interaction *pd.DataFrame*, whose columns are *["userId", "movieId", "rating", "timestamp"]*.

Return type

DataFrame

irspack.dataset.MovieLens100KDataManager

class irspack.dataset.**MovieLens100KDataManager**(*zippath=None*, *force_download=False*)

Bases: BaseMovieLenstDataLoader

Manages MovieLens 100K dataset.

Parameters

- **zippath** (*Optional[Union[Path, str]]*) – Where the zipped data is located. If *None*, assumes the path to be *~/.ml-1m.zip*. If the designated path does not exist, you will be prompted for the permission to download the data. Defaults to *None*.
- **force_download** (*bool*) – If *True*, the class will not prompt for the permission and start downloading immediately.

__init__(*zippath=None*, *force_download=False*)

Specify the zip path for dataset. If that path does not exist, try downloading the relevant data from online resources.

Parameters

- **zippath** (*Optional[Union[Path, str]], optional*) – _description_. Defaults to None.
- **force_download** (*bool, optional*) – _description_. Defaults to False.

Raises

RuntimeError – _description_

Methods

__init__([zippath, force_download])	Specify the zip path for dataset.
read_interaction()	Reads the entire user/movie/rating/timestamp interaction data.
read_item_info()	
read_user_info()	

Attributes

DEFAULT_PATH
DOWNLOAD_URL
GENRE_PATH
INTERACTION_PATH
ITEM_INFO_PATH
USER_INFO_PATH

read_interaction()

Reads the entire user/movie/rating/timestamp interaction data.

Returns
The interaction *pd.DataFrame*, whose columns are *["userId", "movieId", "rating", "timestamp"]*.

Return type
DataFrame

irspack.dataset.MovieLens20MDataManager

class irspack.dataset.**MovieLens20MDataManager**(*zippath=None*, *force_download=False*)

Bases: BaseMovieLenstDataLoader

Parameters

- **zippath** (*Optional[Union[Path, str]]*) –
- **force_download** (*bool*) –

__init__(*zippath=None*, *force_download=False*)

Specify the zip path for dataset. If that path does not exist, try downloading the relevant data from online resources.

Parameters

- **zippath** (*Optional[Union[Path, str]], optional*) – _description_. Defaults to None.
- **force_download** (*bool, optional*) – _description_. Defaults to False.

Raises
RuntimeError – _description_

Methods

__init__([zippath, force_download])	Specify the zip path for dataset.
read_interaction()	Reads the entire user/movie/rating/timestamp interaction data.

Attributes

DEFAULT_PATH
DOWNLOAD_URL
INTERACTION_PATH

read_interaction()

Reads the entire user/movie/rating/timestamp interaction data.

Returns

The interaction *pd.DataFrame*, whose columns are *["userId", "movieId", "rating", "timestamp"]*.

Return type

DataFrame

irspack.dataset.NeuMFML1MDownloader

class irspack.dataset.**NeuMFML1MDownloader**(*zippath=None*, *force_download=False*)

Bases: NeuMFDownloader

Manages MovieLens 1M dataset split under 1-vs-100 negative evaluation protocol.

Parameters

- **zippath** (*Optional[Union[Path, str]]*) – Where the zipped data is located. If *None*, assumes the path to be *~/.neumf-ml-1m.zip*. If the designated path does not exist, you will be prompted for the permission to download the data. Defaults to *None*.
- **force_download** (*bool*) – If *True*, the class will not prompt for the permission and start downloading immediately.

__init__(*zippath=None*, *force_download=False*)

Specify the zip path for dataset. If that path does not exist, try downloading the relevant data from online resources.

Parameters

- **zippath** (*Optional[Union[Path, str]], optional*) – _description_. Defaults to None.
- **force_download** (*bool, optional*) – _description_. Defaults to False.

Raises

RuntimeError – _description_

Methods

__init__([zippath, force_download])	Specify the zip path for dataset.
read_train_test()	

Attributes

DEFAULT_PATH
NEGATIVE_URL
TRAIN_URL

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