LensKit Documentation

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Contents:

LensKit is a set of Python tools for experimenting with and studying recommender systems. It provides support for training, running, and evaluating recommender algorithms in a flexible fashion suitable for research and education.

LensKit for Python (also known as LKPY) is the successor to the Java-based LensKit project.

CHAPTER 1

Installation

To install the current release with Anaconda (recommended):

```
conda install -c lenskit lenskit
```

Or you can use `pip`:

```
pip install lenskit
```

To use the latest development version, install directly from GitHub:

```
pip install git+https://github.com/lenskit/lkpy
```

Then see Getting Started.

CHAPTER 2

Resources

- Mailing list, etc.
- Source and issues on GitHub

2.1 Getting Started

This notebook gets you started with a brief nDCG evaluation with LensKit for Python.

2.1.1 Setup

We first import the LensKit components we need:

[1]:
```
from lenskit import batch, topn
from lenskit import crossfold as xf
from lenskit.algorithms import als, item_knn as knn
from lenskit.metrics import topn as tnmetrics
```

And Pandas is very useful:

[2]:
```
import pandas as pd
```

[3]:
```
%matplotlib inline
```

2.1.2 Loading Data

We're going to use the ML-100K data set:

[4]:
```
ratings = pd.read_csv('ml-100k/u.data', sep='\t',
                      names=['user', 'item', 'rating', 'timestamp'])
ratings.head()
```

[4]:

```
   user  item  rating  timestamp
0   196   242       3  881250949
1   186   302       3  891717742
2    22   377       1  878887116
3   244    51       2  880606923
4   166   346       1  886397596
```

2.1.3 Defining Algorithms

Let's set up two algorithms:

[5]:

```
algo_ii = knn.ItemItem(20)
algo_als = als.BiasedMF(50)
```

2.1.4 Running the Evaluation

In LensKit, our evaluation proceeds in 2 steps:

1. Generate recommendations
2. Measure them

If memory is a concern, we can measure while generating, but we will not do that for now.

We will first define a function to generate recommendations from one algorithm over a single partition of the data set. It will take an algorithm, a train set, and a test set, and return the recommendations:

[6]:

```
def eval(aname, algo, train, test):
    model = algo.train(train)
    users = test.user.unique()
    # the recommend function can merge rating values
    recs = batch.recommend(algo, model, users, 100,
            topn.UnratedCandidates(train), test)
    # add the algorithm
    recs['Algorithm'] = aname
    return recs
```

Now, we will loop over the data and the algorithms, and generate recommendations:

[7]:

```
all_recs = []
for train, test in xf.partition_users(ratings, 5, xf.SampleFrac(0.2)):
    all_recs.append(eval('ItemItem', algo_ii, train, test))
    all_recs.append(eval('ALS', algo_als, train, test))
```

With the results in place, we can concatenate them into a single data frame:

[8]:

```
all_recs = pd.concat(all_recs)
all_recs.head()
```

[8]:

```
   user  rank  item     score  rating    timestamp Algorithm
0     6     1  1449  4.975959     0.0          NaN  ItemItem
1     6     2  1398  4.693661     0.0          NaN  ItemItem
2     6     3   603  4.583224     0.0          NaN  ItemItem
3     6     4   480  4.449822     4.0  883601089.0  ItemItem
4     6     5  1642  4.422142     0.0          NaN  ItemItem
```

nDCG is a per-user metric. Let's compute it for each user. The `` ` ``ndcg <evaluation.rst#lenskit.metrics.topn.ndcg>`__ function has two versions; the version we are using takes a vector of ratings, in order of rank, and computes the nDCG. We can apply this to the rating vector from each user's recommendations for each algorithm. We assume that each user only appears once per algorithm.

[9]:
```
user_ndcg = all_recs.groupby(['Algorithm', 'user']).rating.apply(tnmetrics.ndcg)
user_ndcg.head()
```

[9]:
```
Algorithm  user
ALS        1       0.462178
           2       0.170707
           3       0.508433
           4       0.000000
           5       0.428571
Name: rating, dtype: float64
```

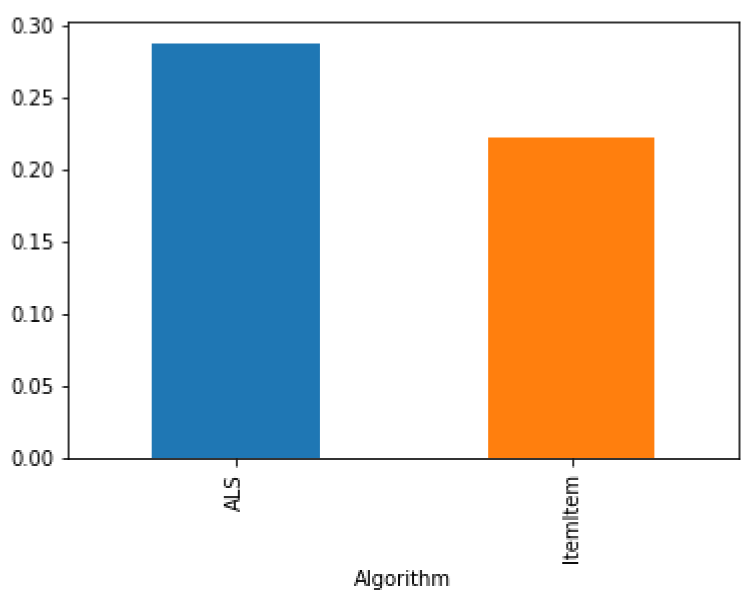
Now we have a *series*, indexed by algorithm and user, with each user's nDCG. If we want to compare the algorithms, we can take the average:

[10]:
```
user_ndcg.groupby('Algorithm').mean()
```

[10]:
```
Algorithm
ALS         0.287846
ItemItem    0.221686
Name: rating, dtype: float64
```

[11]:
```
user_ndcg.groupby('Algorithm').mean().plot.bar()
```

[11]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x24068ad6b00>
```



[ ]:

2.2 Crossfold preparation

The LKPY *crossfold* module provides support for preparing data sets for cross-validation. Crossfold methods are implemented as functions that operate on data frames and return generators of *(train, test)* pairs (`lenskit.crossfold.TTPair` objects). The train and test objects in each pair are also data frames, suitable for evaluation or writing out to a file.

Crossfold methods make minimal assumptions about their input data frames, so the frames can be ratings, purchases, or whatever. They do assume that each row represents a single data point for the purpose of splitting and sampling.

Experiment code should generally use these functions to prepare train-test files for training and evaluating algorithms. For example, the following will perform a user-based 5-fold cross-validation as was the default in the old LensKit:

```
import pandas as pd
import lenskit.crossfold as xf
ratings = pd.read_csv('ml-20m/ratings.csv')
ratings = ratings.rename(columns={'userId': 'user', 'movieId': 'item'})
for i, tp in enumerate(xf.partition_users(ratings, 5, xf.SampleN(5))):
    tp.train.to_csv('ml-20m.exp/train-%d.csv' % (i,))
    tp.train.to_parquet('ml-20m.exp/train-%d.parquet % (i,))
    tp.test.to_csv('ml-20m.exp/test-%d.csv' % (i,))
    tp.test.to_parquet('ml-20m.exp/test-%d.parquet % (i,))
```

2.2.1 Row-based splitting

The simplest preparation methods sample or partition the rows in the input frame. A 5-fold `partition_rows()` split will result in 5 splits, each of which extracts 20% of the rows for testing and leaves 80% for training.

`lenskit.crossfold.`**`partition_rows`**(*data*, *partitions*)

Partition a frame of ratings or other datainto train-test partitions. This function does not care what kind of data is in *data*, so long as it is a Pandas DataFrame (or equivalent).

Parameters

- **data** (`pandas.DataFrame` or equivalent) – a data frame containing ratings or other data you wish to partition.
- **partitions** (*integer*) – the number of partitions to produce

Return type iterator

Returns an iterator of train-test pairs

`lenskit.crossfold.`**`sample_rows`**(*data*, *partitions*, *size*, *disjoint=True*)

Sample train-test a frame of ratings into train-test partitions. This function does not care what kind of data is in *data*, so long as it is a Pandas DataFrame (or equivalent).

Parameters

- **data** (`pandas.DataFrame` or equivalent) – a data frame containing ratings or other data you wish to partition.
- **partitions** (*integer*) – the number of partitions to produce

Return type iterator

Returns an iterator of train-test pairs

2.2.2 User-based splitting

It's often desirable to use users, instead of raw rows, as the basis for splitting data. This allows you to control the experimental conditions on a user-by-user basis, e.g. by making sure each user is tested with the same number of ratings. These methods require that the input data frame have a *user* column with the user names or identifiers.

The algorithm used by each is as follows:

1. Sample or partition the set of user IDs into *n* sets of test users.
2. For each set of test users, select a set of that user's rows to be test rows.
3. **Create a training set for each test set consisting of the non-selected rows from each** of that set's test users, along with all rows from each non-test user.

`lenskit.crossfold.`**`partition_users`**(*data*, *partitions: int*, *method: lenskit.crossfold.PartitionMethod*)

Partition a frame of ratings or other data into train-test partitions user-by-user. This function does not care what kind of data is in *data*, so long as it is a Pandas DataFrame (or equivalent) and has a *user* column.

Parameters

- **`data`** (`pandas.DataFrame` or equivalent) – a data frame containing ratings or other data you wish to partition.
- **`partitions`** (*`integer`*) – the number of partitions to produce
- **`method`** – The method for selecting test rows for each user.

Return type iterator

Returns an iterator of train-test pairs

`lenskit.crossfold.`**`sample_users`**(*data*, *partitions: int*, *size: int*, *method: lenskit.crossfold.PartitionMethod*, *disjoint=True*)

Create train-test partitions by sampling users. This function does not care what kind of data is in *data*, so long as it is a Pandas DataFrame (or equivalent) and has a *user* column.

Parameters

- **`data`** (`pandas.DataFrame` or equivalent) – a data frame containing ratings or other data you wish to partition.
- **`partitions`** – the number of partitions to produce
- **`size`** – the sample size
- **`method`** – The method for selecting test rows for each user.
- **`disjoint`** – whether user samples should be disjoint

Return type iterator

Returns an iterator of train-test pairs

Selecting user test rows

These functions each take a *method* to decide how select each user's test rows. The method is a function that takes a data frame (containing just the user's rows) and returns the test rows. This function is expected to preserve the index of the input data frame (which happens by default with common means of implementing samples).

We provide several partition method factories:

`lenskit.crossfold.`**`SampleN`**(*n*)

Randomly select a fixed number of test rows per user/item.

Parameters **n** – The number of test items to select.

`lenskit.crossfold.`**`SampleFrac`**(*frac*)
Randomly select a fraction of test rows per user/item.

Parameters **frac** – the fraction of items to select for testing.

`lenskit.crossfold.`**`LastN`**(*n*, *col='timestamp'*)
Select a fixed number of test rows per user/item, based on ordering by a column.

Parameters

- **n** – The number of test items to select.
- **col** – The column to sort by.

`lenskit.crossfold.`**`LastFrac`**(*frac*, *col='timestamp'*)
Select a fraction of test rows per user/item.

Parameters

- **frac** – the fraction of items to select for testing.
- **col** – The column to sort by.

2.2.3 Utility Classes

class `lenskit.crossfold.`**`PartitionMethod`**
Partition methods select test rows for a user or item. Partition methods are callable; when called with a data frame, they return the test rows.

`__call__`(*udf*)
Subset a data frame.

Parameters **udf** – The input data frame of rows for a user or item.

Returns The data frame of test rows, a subset of *udf*.

class `lenskit.crossfold.`**`TTPair`**
Train-test pair (named tuple).

`test`
Test data for this pair.

`train`
Train data for this pair.

2.3 Batch-Running Recommendations

The `lenskit.batch` module contains support for *batch-running* recommender and predictor algorithms. This is often used as part of a recommender evaluation experiment.

2.3.1 Recommendation

`lenskit.batch.`**`recommend`**(*algo*, *model*, *users*, *n*, *candidates*, *ratings=None*, *nprocs=None*)
Batch-recommend for multiple users. The provided algorithm should be a `algorithms.Recommender` or `algorithms.Predictor` (which will be converted to a top-N recommender).

Parameters

- **algo** – the algorithm
- **model** – The algorithm model
- **users** (*array-like*) – the users to recommend for
- **n** (*int*) – the number of recommendations to generate (None for unlimited)
- **candidates** – the users' candidate sets. This can be a function, in which case it will be passed each user ID; it can also be a dictionary, in which case user IDs will be looked up in it.
- **ratings** (*pandas.DataFrame*) – if not `None`, a data frame of ratings to attach to recommendations when available.

Returns A frame with at least the columns `user`, `rank`, and `item`; possibly also `score`, and any other columns returned by the recommender.

2.3.2 Rating Prediction

`lenskit.batch.`**`predict`**(*algo*, *pairs*, *model=None*, *nprocs=None*)

Generate predictions for user-item pairs. The provided algorithm should be a `algorithms.Predictor` or a function of two arguments: the user ID and a list of item IDs. It should return a dictionary or a `pandas.Series` mapping item IDs to predictions.

Parameters

- **or** (*predictor (callable)* – py:class:algorithms.Predictor): a rating predictor function or algorithm.
- **pairs** (*pandas.DataFrame*) – a data frame of (`user`, `item`) pairs to predict for. If this frame also contains a `rating` column, it will be included in the result.
- **model** (*any*) – a model for the algorithm.

Returns a frame with columns `user`, `item`, and `prediction` containing the prediction results. If `pairs` contains a *rating* column, this result will also contain a *rating* column.

Return type pandas.DataFrame

2.3.3 Scripting Evaluation

`class` `lenskit.batch.`**`MultiEval`**(*path*, *predict=True*, *recommend=100*, *candidates=<class 'lenskit.topn.UnratedCandidates'>*, *nprocs=None*)

A runner for carrying out multiple evaluations, such as parameter sweeps.

Parameters

- **path** (str or `pathlib.Path`) – the working directory for this evaluation. It will be created if it does not exist.
- **predict** (*bool*) – whether to generate rating predictions.
- **recommend** (*int*) – the number of recommendations to generate per user (None to disable top-N).
- **candidates** (*function*) – the default candidate set generator for recommendations. It should take the training data and return a candidate generator, itself a function mapping user IDs to candidate sets.

add_algorithms (*algos*, *parallel=False*, *attrs=[]*, ***kwargs*)
Add one or more algorithms to the run.

Parameters

- **algos** (*algorithm or list*) – the algorithm(s) to add.
- **parallel** (*bool*) – if `True`, allow this algorithm to be trained in parallel with others.
- **attrs** (*list of str*) – a list of attributes to extract from the algorithm objects and include in the run descriptions.
- **kwargs** – additional attributes to include in the run descriptions.

add_datasets (*data*, *name=None*, *candidates=None*, ***kwargs*)
Add one or more datasets to the run.

Parameters

- **data** – the input data set(s) to run. Can be one of the followin:
  - A tuple of (train, test) data.
  - An iterable of (train, test) pairs, in which case the iterable is not consumed until it is needed.
  - A function yielding either of the above, to defer data load until it is needed.
- **kwargs** – additional attributes pertaining to these data sets.

run ()
Run the evaluation.

2.4 Evaluating Recommender Output

LensKit's evaluation support is based on post-processing the output of recommenders and predictors. The batch utilities provide support for generating these outputs.

We generally recommend using Jupyter notebooks for evaluation.

2.4.1 Prediction Accuracy Metrics

The `lenskit.metrics.predict` module containins prediction accuracy metrics.

Metric Functions

`lenskit.metrics.predict.`**rmse** (*predictions*, *truth*, *missing='error'*)
Compute RMSE (root mean squared error).

Parameters

- **predictions** (*pandas.Series*) – the predictions
- **truth** (*pandas.Series*) – the ground truth ratings from data
- **missing** (*string*) – how to handle predictions without truth. Can be one of `'error'` or `'ignore'`.

Returns the root mean squared approximation error

Return type double

`lenskit.metrics.predict.`**`mae`**(*predictions*, *truth*, *missing='error'*)
Compute MAE (mean absolute error).

Parameters

- **`predictions`** (*`pandas.Series`*) – the predictions
- **`truth`** (*`pandas.Series`*) – the ground truth ratings from data
- **`missing`** (*`string`*) – how to handle predictions without truth. Can be one of `'error'` or `'ignore'`.

Returns the mean absolute approximation error

Return type double

Working with Missing Data

LensKit rating predictors do not report predictions when their core model is unable to predict. For example, a nearest-neighbor recommender will not score an item if it cannot find any suitable neighbors. Following the Pandas convention, these items are given a score of NaN (when Pandas implements better missing data handling, it will use that, so use `pandas.Series.isna()`/`pandas.Series.notna()`, not the `isnan` versions.

However, this causes problems when computing predictive accuracy: recommenders are not being tested on the same set of items. If a recommender only scores the easy items, for example, it could do much better than a recommender that is willing to attempt more difficult items.

A good solution to this is to use a *fallback predictor* so that every item has a prediction. In LensKit, *`lenskit.algorithms.basic.Fallback`* implements this functionality; it wraps a sequence of recommenders, and for each item, uses the first one that generates a score.

You set it up like this:

```
cf = ItemItem(20)
base = Bias(damping=5)
algo = Fallback(cf, base)
```

2.4.2 Top-*N* Accuracy Metrics

The *`lenskit.metrics.topn`* module contains metrics for evaluating top-*N* recommendation lists.

Classification Metrics

These metrics treat the recommendation list as a classification of relevant items.

`lenskit.metrics.topn.`**`precision`**(*recs*, *relevant*)
Compute the precision of a set of recommendations.

Parameters

- **`recs`** (*`array-like`*) – a sequence of recommended items
- **`relevant`** (*`set-like`*) – the set of relevant items

Returns the fraction of recommended items that are relevant

Return type double

`lenskit.metrics.topn.`**`recall`**(*recs*, *relevant*)
Compute the recall of a set of recommendations.

Parameters

- **recs** (*array-like*) – a sequence of recommended items
- **relevant** (*set-like*) – the set of relevant items

Returns the fraction of relevant items that were recommended.

Return type double

Ranked List Metrics

These metrics treat the recommendation list as a ranked list of items that may or may not be relevant.

`lenskit.metrics.topn.`**`recip_rank`**(*recs*, *relevant*)

Compute the reciprocal rank of the first relevant item in a recommendation list. This is used to compute MRR.

Parameters

- **recs** (*array-like*) – a sequence of recommended items
- **relevant** (*set-like*) – the set of relevant items

Returns the reciprocal rank of the first relevant item.

Return type double

Utility Metrics

The nDCG function estimates a utility score for a ranked list of recommendations.

`lenskit.metrics.topn.`**`ndcg`**(*scores*, *items=None*, *discount=<ufunc 'log2'>*)

Compute the Normalized Discounted Cumulative Gain of a series of scores. These should be relevance scores; they can be $0, 1$ for binary relevance data.

Discounted cumultative gain is computed as:

$$\begin{aligned} \mathrm{DCG}(L,u) &= \sum_{i=1}^{|L|} \frac{r_{ui}}{d(i)} \\ \mathrm{nDCG}(L,u) &= \frac{\mathrm{DCG}(L,u)}{\mathrm{DCG}(L_{\mathrm{ideal}},u)} \end{aligned}$$

Parameters

- **scores** (*pd.Series or array-like*) – relevance scores for items. If `items` is `None`, these should be in order of recommendation; if `items` is not `None`, then this must be a `pandas.Series` indexed by item ID.
- **items** (*array-like*) – the list of item IDs, if the item list and score list is to be provided separately.
- **discount** (*ufunc*) – the rank discount function. Each item's score will be divided the discount of its rank, if the discount is greater than 1.

Returns the nDCG of the scored items.

Return type double

2.4.3 Loading Outputs

We typically store the output of recommendation runs in LensKit experiments in CSV or Parquet files. The *lenskit.batch.MultiEval* class arranges to run a set of algorithms over a set of data sets, and store the results in a collection of Parquet files in a specified output directory.

There are several files:

runs.parquet The _runs_, algorithm-dataset combinations. This file contains the names & any associated properties of each algorithm and data set run, such as a feature count.

recommendations.parquet The recommendations, with columns `RunId`, `user`, `rank`, `item`, and `rating`.

predictions.parquet The rating predictions, if the test data includes ratings.

For example, if you want to examine nDCG by neighborhood count for a set of runs on a single data set, you can do:

```
import pandas as pd
from lenskit.metrics import topn as lm

runs = pd.read_parquet('eval-dir/runs.parquet')
recs = pd.read_parquet('eval-dir/recs.parquet')
meta = runs.loc[:, ['RunId', 'max_neighbors']]

# compute each user's nDCG
user_ndcg = recs.groupby(['RunId', 'user']).rating.apply(lm.ndcg)
user_ndcg = user_ndcg.reset_index(name='nDCG')
# combine with metadata for feature count
user_ndcg = pd.merge(user_ndcg, meta)
# group and aggregate
nbr_ndcg = user_ndcg.groupby('max_neighbors').nDCG.mean()
nbr_ndcg.plot()
```

2.5 Algorithms

LKPY provides general algorithmic concepts, along with implementations of several algorithms.

2.5.1 Algorithm Interfaces

LKPY's batch routines and utility support for managing algorithms expect algorithms to implement consistent interfaces. This page describes those interfaces.

The interfaces are realized as abstract base classes with the Python `abc` module. Implementations must be registered with their interfaces, either by subclassing the interface or by calling `abc.ABCMeta.register()`.

Recommendation

The *Recommender* interface provides an interface to generating recommendations. Not all algorithms implement it; call *Recommender.adapt()* on an algorithm to get a recommender for any algorithm that at least implements *Predictor*. For example:

```
pred = Bias(damping=5)
rec = Recommender.adapt(pred)
```

class `lenskit.algorithms.`**`Recommender`**

Recommends items for a user.

classmethod adapt(*algo*)

Adapt an algorithm to be a recommender.

Parameters **`algo`** – the algorithm to adapt. If the algorithm implements *`Recommender`*, it is returned as-is; if it implements *`Predictor`*, then a top-N recommender using the predictor's scores is returned.

Returns a recommendation interface to `algo`.

Return type *Recommender*

`recommend`(*model*, *user*, *n=None*, *candidates=None*, *ratings=None*)

Compute recommendations for a user.

Parameters

- **`model`** – the trained model to use. Either `None` or the ratings matrix if the algorithm has no concept of training.
- **`user`** – the user ID
- **`n`** (*`int`*) – the number of recommendations to produce (`None` for unlimited)
- **`candidates`** (*`array-like`*) – the set of valid candidate items.
- **`ratings`** (*`pandas.Series`*) – the user's ratings (indexed by item id); if provided, they may be used to override or augment the model's notion of a user's preferences.

Returns a frame with an `item` column; if the recommender also produces scores, they will be in a `score` column.

Return type pandas.DataFrame

Rating Prediction

class `lenskit.algorithms.`**`Predictor`**

Predicts user ratings of items. Predictions are really estimates of the user's like or dislike, and the `Predictor` interface makes no guarantees about their scale or granularity.

`predict`(*model*, *user*, *items*, *ratings=None*)

Compute predictions for a user and items.

Parameters

- **`model`** – the trained model to use. Either `None` or the ratings matrix if the algorithm has no concept of training.
- **`user`** – the user ID
- **`items`** (*`array-like`*) – the items to predict
- **`ratings`** (*`pandas.Series`*) – the user's ratings (indexed by item id); if provided, they may be used to override or augment the model's notion of a user's preferences.

Returns scores for the items, indexed by item id.

Return type pandas.Series

Model Training

Most algorithms have some concept of a trained model. The `Trainable` interface captures the ability of a model to be trained and saved to disk.

class `lenskit.algorithms.`**`Trainable`**

Models that can be trained and have their models saved.

`train`(*ratings*)

Train the model on rating/consumption data. Training methods that require additional data may accept it as additional parameters or via class members.

Parameters **`ratings`** (*`pandas.DataFrame`*) – rating data, as a matrix with columns 'user', 'item', and 'rating'. The user and item identifiers may be of any type.

Returns the trained model (of an implementation-defined type).

`save_model`(*model*, *path*)

Save a trained model to a file or directory. The default implementation pickles the model.

Algorithms are allowed to use any format for saving their models, including directories.

Parameters

- **`model`** – the trained model.
- **`path`** (*`str`*) – the path at which to save the model.

`load_model`(*path*)

Save a trained model to a file.

Parameters **`path`** (*`str`*) – the path to file from which to load the model.

Returns the re-loaded model (of an implementation-defined type).

2.5.2 Basic and Utility Algorithms

The *`lenskit.algorithms.basic`* module contains baseline and utility algorithms for nonpersonalized recommendation and testing.

Personalized Mean Rating Prediction

class `lenskit.algorithms.basic.`**`Bias`**(*items=True*, *users=True*, *damping=0.0*)

Bases: *`lenskit.algorithms.Predictor`*, *`lenskit.algorithms.Trainable`*

A user-item bias rating prediction algorithm. This implements the following predictor algorithm:

$$s(u, i) = \mu + b_i + b_u$$

where μ is the global mean rating, b_i is item bias, and b_u is the user bias. With the provided damping values β_{u} and β_{i}, they are computed as follows:

$$\mu = \frac{\sum_{r_{ui} \in R} r_{ui}}{|R|} \qquad b_i = \frac{\sum_{r_{ui} \in R_i} (r_{ui} - \mu)}{|R_i| + \beta_{\mathrm{i}}} \qquad b_u = \frac{\sum_{r_{ui} \in R_u} (r_{ui} - \mu - b_i)}{|R_u| + \beta_{\mathrm{u}}}$$

The damping values can be interpreted as the number of default (mean) ratings to assume *a priori* for each user or item, damping low-information users and items towards a mean instead of permitting them to take on extreme values based on few ratings.

Parameters

- **items** – whether to compute item biases
- **users** – whether to compute user biases
- **damping** (*number or tuple*) – Bayesian damping to apply to computed biases. Either a number, to damp both user and item biases the same amount, or a (user,item) tuple providing separate damping values.

predict (*model*, *user*, *items*, *ratings=None*)
Compute predictions for a user and items. Unknown users and items are assumed to have zero bias.

Parameters

- **model** (BiasModel) – the trained model to use.
- **user** – the user ID
- **items** (*array-like*) – the items to predict
- **ratings** (*pandas.Series*) – the user's ratings (indexed by item id); if provided, will be used to recompute the user's bias at prediction time.

Returns scores for the items, indexed by item id.

Return type pandas.Series

train (*data*)
Train the bias model on some rating data.

Parameters data (*DataFrame*) – a data frame of ratings. Must have at least *user*, *item*, and *rating* columns.

Returns a trained model with the desired biases computed.

Return type *BiasModel*

class lenskit.algorithms.basic.**BiasModel**
Trained model for the *Bias* algorithm.

mean
the global mean.

Type double

items
the item means.

Type pandas.Series

users
the user means.

Type pandas.Series

Fallback Predictor

The `Fallback` rating predictor is a simple hybrid that takes a list of composite algorithms, and uses the first one to return a result to predict the rating for each item.

A common case is to fill in with *Bias* when a primary predictor cannot score an item.

class lenskit.algorithms.basic.**Fallback** (**algorithms*)
Bases: *lenskit.algorithms.Predictor*, *lenskit.algorithms.Trainable*

The Fallback algorithm predicts with its first component, uses the second to fill in missing values, and so forth.

load_model (*file*)
Save a trained model to a file.

Parameters **path** (*str*) – the path to file from which to load the model.

Returns the re-loaded model (of an implementation-defined type).

predict (*model*, *user*, *items*, *ratings=None*)
Compute predictions for a user and items.

Parameters

- **model** – the trained model to use. Either `None` or the ratings matrix if the algorithm has no concept of training.
- **user** – the user ID
- **items** (*array-like*) – the items to predict
- **ratings** (*pandas.Series*) – the user's ratings (indexed by item id); if provided, they may be used to override or augment the model's notion of a user's preferences.

Returns scores for the items, indexed by item id.

Return type pandas.Series

save_model (*model*, *path*)
Save a trained model to a file or directory. The default implementation pickles the model.

Algorithms are allowed to use any format for saving their models, including directories.

Parameters

- **model** – the trained model.
- **path** (*str*) – the path at which to save the model.

train (*ratings*)
Train the model on rating/consumption data. Training methods that require additional data may accept it as additional parameters or via class members.

Parameters **ratings** (*pandas.DataFrame*) – rating data, as a matrix with columns 'user', 'item', and 'rating'. The user and item identifiers may be of any type.

Returns the trained model (of an implementation-defined type).

Memorized Predictor

The `Memorized` recommender is primarily useful for test cases. It memorizes a set of rating predictions and returns them.

class `lenskit.algorithms.basic.`**Memorized** (*scores*)
Bases: `object`

The memorized algorithm memorizes scores & repeats them.

2.5.3 k-NN Collaborative Filtering

LKPY provides user- and item-based classical k-NN collaborative Filtering implementations. These lightly-configurable implementations are intended to capture the behavior of the Java-based LensKit implementations to provide a good upgrade path and enable basic experiments out of the box.

Item-based k-NN

class `lenskit.algorithms.item_knn.`**`ItemItem`**(*nnbrs*, *min_nbrs=1*, *min_sim=1e-06*, *save_nbrs=None*, *center=True*, *aggregate='weighted-average'*)

Bases: `lenskit.algorithms.Trainable`, `lenskit.algorithms.Predictor`

Item-item nearest-neighbor collaborative filtering with ratings. This item-item implementation is not terribly configurable; it hard-codes design decisions found to work well in the previous Java-based LensKit code.

`load_model`(*path*)

Save a trained model to a file.

Parameters **`path`** (`str`) – the path to file from which to load the model.

Returns the re-loaded model (of an implementation-defined type).

`predict`(*model*, *user*, *items*, *ratings=None*)

Compute predictions for a user and items.

Parameters

- **`model`** – the trained model to use. Either `None` or the ratings matrix if the algorithm has no concept of training.
- **`user`** – the user ID
- **`items`** (`array-like`) – the items to predict
- **`ratings`** (`pandas.Series`) – the user's ratings (indexed by item id); if provided, they may be used to override or augment the model's notion of a user's preferences.

Returns scores for the items, indexed by item id.

Return type pandas.Series

`save_model`(*model*, *path*)

Save a trained model to a file or directory. The default implementation pickles the model.

Algorithms are allowed to use any format for saving their models, including directories.

Parameters

- **`model`** – the trained model.
- **`path`** (`str`) – the path at which to save the model.

`train`(*ratings*)

Train a model.

The model-training process depends on `save_nbrs` and `min_sim`, but *not* on other algorithm parameters.

Parameters **`ratings`** (`pandas.DataFrame`) – (user,item,rating) data for computing item similarities.

Returns a trained item-item CF model.

class `lenskit.algorithms.item_knn.`**`IIModel`**

Item-item recommendation model. This stores the necessary data to run the item-based k-NN recommender.

`items`

the index of item IDs.

Type pandas.Index

means
the mean rating for each known item.

Type numpy.ndarray

counts
the number of saved neighbors for each item.

Type numpy.ndarray

sim_matrix
the similarity matrix.

Type *matrix.CSR*

users
the index of known user IDs for the rating matrix.

Type pandas.Index

rating_matrix
the user-item rating matrix for looking up users' ratings.

Type *matrix.CSR*

User-based k-NN

class lenskit.algorithms.user_knn.**UserUser**(*nnbrs*, *min_nbrs=1*, *min_sim=0*, *center=True*, *aggregate='weighted-average'*)

Bases: `lenskit.algorithms.Trainable`, `lenskit.algorithms.Predictor`

User-user nearest-neighbor collaborative filtering with ratings. This user-user implementation is not terribly configurable; it hard-codes design decisions found to work well in the previous Java-based LensKit code.

load_model(*path*)
Save a trained model to a file.

Parameters **path** (`str`) – the path to file from which to load the model.

Returns the re-loaded model (of an implementation-defined type).

predict(*model*, *user*, *items*, *ratings=None*)
Compute predictions for a user and items.

Parameters

- **model** (`UUModel`) – the memorized data to use.
- **user** – the user ID
- **items** (`array-like`) – the items to predict
- **ratings** (`pandas.Series`) – the user's ratings (indexed by item id); if provided, will be used to recompute the user's bias at prediction time.

Returns scores for the items, indexed by item id.

Return type pandas.Series

save_model(*model*, *path*)
Save a trained model to a file or directory. The default implementation pickles the model.

Algorithms are allowed to use any format for saving their models, including directories.

Parameters

- **model** – the trained model.
- **path** (*str*) – the path at which to save the model.

train (*ratings*)

"Train" a user-user CF model. This memorizes the rating data in a format that is usable for future computations.

Parameters **ratings** (*pandas.DataFrame*) – (user, item, rating) data for collaborative filtering.

Returns a memorized model for efficient user-based CF computation.

Return type *UUModel*

class lenskit.algorithms.user_knn.**UUModel**

Memorized data for user-user collaborative filtering.

matrix

normalized user-item rating matrix.

Type *matrix.CSR*

users

index of user IDs.

Type pandas.Index

user_means

user mean ratings.

Type numpy.ndarray

items

index of item IDs.

Type pandas.Index

transpose

the transposed rating matrix (with data transformations but without L2 normalization).

Type *matrix.CSR*

2.5.4 Classic Matrix Factorization

LKPY provides classical matrix factorization implementations.

Common Support

The mf_common module contains common support code for matrix factorization algorithms.

class lenskit.algorithms.mf_common.**MFModel** (*users*, *items*, *umat*, *imat*)

Common model for matrix factorization.

user_index
Users in the model (length=:math:*m*).

Type pandas.Index

item_index
Items in the model (length=:math:*n*).

Type pandas.Index

user_features
The $m \times k$ user-feature matrix.

Type numpy.ndarray

item_features
The $n \times k$ item-feature matrix.

Type numpy.ndarray

lookup_items (*items*)
Look up the indices for a set of items.

Parameters **items** (*array-like*) – the item IDs to look up.

Returns the item indices. Unknown items will have negative indices.

Return type numpy.ndarray

lookup_user (*user*)
Look up the index for a user.

Parameters **user** – the user ID to look up

Returns the user index.

Return type int

n_features
The number of features.

n_items
The number of items.

n_users
The number of users.

score (*user*, *items*)
Score a set of items for a user. User and item parameters must be indices into the matrices.

Parameters

- **user** (*int*) – the user index
- **items** (*array-like of int*) – the item indices
- **raw** (*bool*) – if `True`, do return raw scores without biases added back.

Returns the scores for the items.

Return type numpy.ndarray

class `lenskit.algorithms.mf_common.`**BiasMFModel** (*users*, *items*, *bias*, *umat*, *imat*)
Common model for biased matrix factorization.

user_index
Users in the model (length=:math:*m*).

Type pandas.Index

item_index
Items in the model (length=:math:*n*).

Type pandas.Index

global_bias
The global bias term.

Type double

user_bias
The user bias terms.

Type numpy.ndarray

item_bias
The item bias terms.

Type numpy.ndarray

user_features
The $m \times k$ user-feature matrix.

Type numpy.ndarray

item_features
The $n \times k$ item-feature matrix.

Type numpy.ndarray

score (*user*, *items*, *raw=False*)
Score a set of items for a user. User and item parameters must be indices into the matrices.

Parameters

- **user** (*int*) – the user index
- **items** (*array-like of int*) – the item indices
- **raw** (*bool*) – if `True`, do return raw scores without biases added back.

Returns the scores for the items.

Return type numpy.ndarray

Alternating Least Squares

LensKit provides alternating least squares implementations of matrix factorization suitable for explicit feedback data. These implementations are parallelized with Numba, and perform best with the MKL from Conda.

class `lenskit.algorithms.als.`**BiasedMF** (*features*, *iterations=20*, *reg=0.1*, *damping=5*)
Biased matrix factorization trained with alternating least squares [ZWSP2008]. This is a prediction-oriented algorithm suitable for explicit feedback data.

Parameters

- **features** (*int*) – the number of features to train
- **iterations** (*int*) – the number of iterations to train
- **reg** (*double*) – the regularization factor
- **damping** (*double*) – damping factor for the underlying mean

features
the number of features.

Type int

iterations
the number of training iterations.

Type int

regularization
the regularization factor.

Type double

damping
the mean damping.

Type double

load_model(*path*)
Save a trained model to a file.

Parameters **path** (*str*) – the path to file from which to load the model.

Returns the re-loaded model (of an implementation-defined type).

predict(*model: lenskit.algorithms.mf_common.BiasMFModel*, *user*, *items*, *ratings=None*)
Compute predictions for a user and items.

Parameters

- **model** – the trained model to use. Either `None` or the ratings matrix if the algorithm has no concept of training.
- **user** – the user ID
- **items** (*array-like*) – the items to predict
- **ratings** (*pandas.Series*) – the user's ratings (indexed by item id); if provided, they may be used to override or augment the model's notion of a user's preferences.

Returns scores for the items, indexed by item id.

Return type pandas.Series

save_model(*model*, *path*)
Save a trained model to a file or directory. The default implementation pickles the model.

Algorithms are allowed to use any format for saving their models, including directories.

Parameters

- **model** – the trained model.
- **path** (*str*) – the path at which to save the model.

train(*ratings*, *bias=None*)
Run ALS to train a model.

Parameters

- **ratings** – the ratings data frame.
- **bias** (*bias.BiasModel*) – a pre-trained bias model to use.

Returns The trained biased MF model.

Return type *BiasMFModel*

class `lenskit.algorithms.als.`**`ImplicitMF`**(*features*, *iterations=20*, *reg=0.1*, *weight=40*)

Implicit matrix factorization trained with alternating least squares [HKV2008]. This algorithm outputs 'predictions', but they are not on a meaningful scale. If its input data contains `rating` values, these will be used as the 'confidence' values; otherwise, confidence will be 1 for every rated item.

Parameters

- **`features`** (*`int`*) – the number of features to train
- **`iterations`** (*`int`*) – the number of iterations to train
- **`reg`** (*`double`*) – the regularization factor
- **`weight`** (*`double`*) – the scaling weight for positive samples (α in [HKV2008]).

`load_model`(*path*)

Save a trained model to a file.

Parameters **`path`** (*`str`*) – the path to file from which to load the model.

Returns the re-loaded model (of an implementation-defined type).

`predict`(*model: lenskit.algorithms.mf_common.MFModel*, *user*, *items*, *ratings=None*)

Compute predictions for a user and items.

Parameters

- **`model`** – the trained model to use. Either `None` or the ratings matrix if the algorithm has no concept of training.
- **`user`** – the user ID
- **`items`** (*`array-like`*) – the items to predict
- **`ratings`** (*`pandas.Series`*) – the user's ratings (indexed by item id); if provided, they may be used to override or augment the model's notion of a user's preferences.

Returns scores for the items, indexed by item id.

Return type pandas.Series

`save_model`(*model*, *path*)

Save a trained model to a file or directory. The default implementation pickles the model.

Algorithms are allowed to use any format for saving their models, including directories.

Parameters

- **`model`** – the trained model.
- **`path`** (*`str`*) – the path at which to save the model.

`train`(*ratings*)

Train the model on rating/consumption data. Training methods that require additional data may accept it as additional parameters or via class members.

Parameters **`ratings`** (*`pandas.DataFrame`*) – rating data, as a matrix with columns 'user', 'item', and 'rating'. The user and item identifiers may be of any type.

Returns the trained model (of an implementation-defined type).

FunkSVD

FunkSVD is an SVD-like matrix factorization that uses stochastic gradient descent, configured much like coordinate descent, to train the user-feature and item-feature matrices.

class `lenskit.algorithms.funksvd.`**`FunkSVD`**(*features*, *iterations=100*, *lrate=0.001*, *reg=0.015*, *damping=5*, *range=None*)

Algorithm class implementing FunkSVD matrix factorization.

Parameters

- **features** (*int*) – the number of features to train
- **iterations** (*int*) – the number of iterations to train each feature
- **lrate** (*double*) – the learning rate
- **reg** (*double*) – the regularization factor
- **damping** (*double*) – damping factor for the underlying mean
- **range** (*tuple*) – the `(min, max)` rating values to clamp ratings, or `None` to leave predictions unclamped.

load_model(*path*)

Save a trained model to a file.

Parameters path (*str*) – the path to file from which to load the model.

Returns the re-loaded model (of an implementation-defined type).

predict(*model*, *user*, *items*, *ratings=None*)

Compute predictions for a user and items.

Parameters

- **model** – the trained model to use. Either `None` or the ratings matrix if the algorithm has no concept of training.
- **user** – the user ID
- **items** (*array-like*) – the items to predict
- **ratings** (*pandas.Series*) – the user's ratings (indexed by item id); if provided, they may be used to override or augment the model's notion of a user's preferences.

Returns scores for the items, indexed by item id.

Return type pandas.Series

save_model(*model*, *path*)

Save a trained model to a file or directory. The default implementation pickles the model.

Algorithms are allowed to use any format for saving their models, including directories.

Parameters

- **model** – the trained model.
- **path** (*str*) – the path at which to save the model.

train(*ratings*, *bias=None*)

Train a FunkSVD model.

Parameters

- **ratings** – the ratings data frame.

- **bias** (*bias.BiasModel*) – a pre-trained bias model to use.

Returns The trained biased MF model.

2.5.5 Hierarchical Poisson Factorization

This module provides a LensKit bridge to the hpfrec library implementing hierarchical Poisson factorization [GHB2013].

class lenskit.algorithms.hpf.**HPF**(*features*, ***kwargs*)
Hierarchical Poisson factorization, provided by hpfrec.

Parameters

- **features** (*int*) – the number of features
- ****kwargs** – arguments passed to `hpfrec.HPF`.

predict(*model: lenskit.algorithms.mf_common.MFModel*, *user*, *items*, *ratings=None*)
Compute predictions for a user and items.

Parameters

- **model** – the trained model to use. Either `None` or the ratings matrix if the algorithm has no concept of training.
- **user** – the user ID
- **items** (*array-like*) – the items to predict
- **ratings** (*pandas.Series*) – the user's ratings (indexed by item id); if provided, they may be used to override or augment the model's notion of a user's preferences.

Returns scores for the items, indexed by item id.

Return type pandas.Series

train(*ratings*)
Train the model on rating/consumption data. Training methods that require additional data may accept it as additional parameters or via class members.

Parameters **ratings** (*pandas.DataFrame*) – rating data, as a matrix with columns 'user', 'item', and 'rating'. The user and item identifiers may be of any type.

Returns the trained model (of an implementation-defined type).

2.6 Utility Functions

Miscellaneous utility functions.

2.6.1 Matrix Utilities

We have some matrix-related utilities, since matrices are used so heavily in recommendation algorithms.

Building Ratings Matrices

`lenskit.matrix.`**`sparse_ratings`**(*ratings*, *scipy=False*)

Convert a rating table to a sparse matrix of ratings.

Parameters

- **`ratings`** (*`pandas.DataFrame`*) – a data table of (user, item, rating) triples.
- **`scipy`** – if `True`, return a SciPy matrix instead of *`CSR`*.

Returns a named tuple containing the sparse matrix, user index, and item index.

Return type *RatingMatrix*

`class` `lenskit.matrix.`**`RatingMatrix`**

A rating matrix with associated indices.

`matrix`

The rating matrix, with users on rows and items on columns.

Type *CSR* or scipy.sparse.csr_matrix

`users`

mapping from user IDs to row numbers.

Type pandas.Index

`items`

mapping from item IDs to column numbers.

Type pandas.Index

Compressed Sparse Row Matrices

We use CSR-format sparse matrices in quite a few places. Since SciPy's sparse matrices are not directly usable from Numba, we have implemented a Numba-compiled CSR representation that can be used from accelerated algorithm implementations.

`lenskit.matrix.`**`csr_from_coo`**(*rows*, *cols*, *vals*, *shape=None*)

Create a CSR matrix from data in COO format.

Parameters

- **`rows`** (*`array-like`*) – the row indices.
- **`cols`** (*`array-like`*) – the column indices.
- **`vals`** (*`array-like`*) – the data values; can be `None`.
- **`shape`** (*`tuple`*) – the array shape, or `None` to infer from row & column indices.

`lenskit.matrix.`**`csr_from_scipy`**(*mat*, *copy=True*)

Convert a scipy sparse matrix to an internal CSR.

Parameters

- **`mat`** (*`scipy.sparse.spmatrix`*) – a SciPy sparse matrix.
- **`copy`** (*`bool`*) – if `False`, reuse the SciPy storage if possible.

Returns a CSR matrix.

Return type *CSR*

`lenskit.matrix.csr_to_scipy(mat)`

Convert a CSR matrix to a SciPy `scipy.sparse.csr_matrix`.

Parameters **mat** (CSR) – A CSR matrix.

Returns A SciPy sparse matrix with the same data. It shares storage with `matrix`.

Return type scipy.sparse.csr_matrix

`lenskit.matrix.csr_rowinds(csr)`

Get the row indices for a CSR matrix.

Parameters **csr** (CSR) – a CSR matrix.

Returns the row index array for the CSR matrix.

Return type np.ndarray

`lenskit.matrix.csr_save(csr: numba.jitclass.base.CSR, prefix=None)`

Extract data needed to save a CSR matrix. This is intended to be used with, for example, **:py:fun:‘numpy.savez‘** to save a matrix:

```
np.savez_compressed('file.npz', **csr_save(csr))
```

The `prefix` allows multiple matrices to be saved in a single file:

```
data = {}
data.update(csr_save(m1, prefix='m1'))
data.update(csr_save(m2, prefix='m2'))
np.savez_compressed('file.npz', **data)
```

Parameters

- **csr** (CSR) – the matrix to save.
- **prefix** (*str*) – the prefix for the data keys.

Returns a dictionary of data to save the matrix.

Return type dict

`lenskit.matrix.csr_load(data, prefix=None)`

Rematerialize a CSR matrix from loaded data. The inverse of **:py:fun:‘csr_save‘**.

Parameters

- **data** (*dict-like*) – the input data.
- **prefix** (*str*) – the prefix for the data keys.

Returns the matrix described by `data`.

Return type *CSR*

class `lenskit.matrix.CSR(nrows, ncols, nnz, ptrs, inds, vals)`

Simple compressed sparse row matrix. This is like `scipy.sparse.csr_matrix`, with a couple of useful differences:

- It is a Numba jitclass, so it can be directly used from Numba-optimized functions.
- The value array is optional, for cases in which only the matrix structure is required.
- The value array, if present, is always double-precision.

You generally don’t want to create this class yourself. Instead, use one of the related utility functions.

nrows
the number of rows.

Type int

ncols
the number of columns.

Type int

nnz
the number of entries.

Type int

rowptrs
the row pointers.

Type numpy.ndarray

colinds
the column indices.

Type numpy.ndarray

values
the values

Type numpy.ndarray

CHAPTER 3

Indices and tables

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- modindex
- search

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