
## Implemented Methods

### Rating Prediction

- averages: global, user, item
- linear baseline method by Koren and Bell
- frequency-weighted Slope One
- k-nearest neighbor (kNN):
  - based on user or item similarities, with different similarity measures
  - collaborative or attribute-/content-based
- (biased) matrix factorization

### Item Prediction

- random
- most popular item
- linear content-based model optimized for Bayesian Personalized Ranking (BPR-Linear)
- support-vector machine using item attributes
- k-nearest neighbor (kNN):
  - based on user or item similarities
  - collaborative or attribute-/content-based
- weighted regularized matrix factorization (WR-MF)
- matrix factorization optimized for Bayesian Personalized Ranking (BPR-MF)


## Download

Get the latest release of MyMediaLite here:

`http://ismll.de/mymedialite`

## Contact

We are always happy about feedback (suggestions, bug reports, patches, etc.). To contact us, send an e-mail to

`mymedialite@ismll.de`

Follow us on Twitter: `@mymedialite`

## Acknowledgements

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# MyMediaLite – Recommender System Algorithm Library

Machine Learning Lab

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MyMediaLite is a lightweight, multi-purpose library of recommender system algorithms. It addresses the two most common scenarios in collaborative filtering: **rating prediction** (e.g. on a scale of 1 to 5 stars) and **item prediction from implicit feedback** (e.g. from clicks or purchase actions).

`http://ismll.de/mymedialite`


# MyMediaLite's Key Features

- **Choice:**
  - Dozens of different recommender engines (see list on this flyer),
  - methods can use collaborative and attribute/content data.
- **Ready to use:**
  - Includes evaluation routines for rating and item prediction; quality measures MAE, NMAE, RMSE, AUC, prec@N, MAP, NDCG; and
  - command line tools that read a simple text-based input format (compatible with the one used by Apache Mahout).
- **Compact:** Core library is around 100 KB "big".
- **Portable:** Written in C#, for the .NET platform; runs on every architecture where Mono works: Linux, Windows, Mac OS X.
- **Free:** Free/Open Source software, distributed under the terms of the GNU General Public License (GPL).
- **Serialization:** save and reload recommender engine models.
- **Real-time online updates** for most models.


# Target Groups

## Researchers

- Don't waste your time implementing methods if you actually want to study other aspects of recommender systems!
- Use the engines as baseline methods in benchmarks.
- Use MyMediaLite's infrastructure as an easy starting point to implement your own methods.

## Developers

- Add recommender system technologies to your software or website.

## Educators and Students

- Demonstrate/see how recommender system methods are implemented.
- Use MyMediaLite as a basis for you school projects.


# Recommendation Tasks Addressed

## Rating Prediction

Popularized by systems like MovieLens, Netflix, or Jester, this is the most-discussed collaborative filtering task in the recommender systems literature. Given a set of ratings, e.g. on a scale from 1 to 5, the goal is predict unknown ratings.

| | *Alice* | *Ben* | *Christine* |
|---|---|---|---|
| *The Usual Suspects* | 5 | | 4 |
| *American Beauty* | 3 | 4 | 3 |
| *The Godfather* | | ?? | 1 |
| *Road Trip* | 2 | | |

## Implicit Feedback Item Recommendation

Getting ratings from users requires explicit actions from their side. Much more data is available in the form of implicit feedback, e.g. whether a user has viewed or purchased a product in an online shop. Very often this information is positive-only, i.e. we know users like the products they buy, but we cannot easily assume that they do not like everything they have not (yet) bought.