

## **Implemented Methods**

### **Rating Prediction**

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

#### Item Prediction

- random
- most popular Iiem
- linear content-based model optimized for Bayesian Personalized Ranking (BPR-Linear)
- 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 would like to get feedback (suggestions, bug reports, etc.) about MyMediaLite. To contact us, send an e-mail to

mymedialite@ismll.de

## Acknowledgements

MyMediaLite was developed by Zeno Gantner, Steffen Rendle, and Christoph Freudenthaler at University of Hildesheim.



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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/



# Recommendation Tasks Addressed

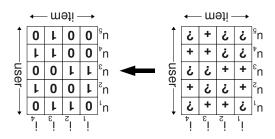
## Rating Prediction

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

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## Implicit Feedback Item Recommendation

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





## Target Groups

### Researchers

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

## Developers

your software. Add recommender system technologies to

#### Students

- ods are implement. See how typical recommender system meth-
- projects. Use MyMediaLite as a basis for you school



# MyMediaLite's Key Features

- Choice:
- (see list on this flyer), Dozens of different recommender engines
- tribute/content data. - methods can use collaborative and at-
- Serialization: save and reload recommender
- Real-time online updates for most models.
- Ready to use:

engine models.

- command line tools that read a simple RMSE, AUC, prec@N, MAP, NDCG; and item prediction; quality measures MAE, - Includes evaluation routines for rating and
- Compact: Core library is 85KB "big".

text-based input format.

- works: Linux, Windows, Mac OS X. form; runs on every architecture where Mono • Portable: Written in C#, for the .NET plat-
- License (GPL). under the terms of the GNU General Public • Free: Free/Open Source software, distributed