



## 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 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 would like to get feedback (suggestions, bug reports, etc.) about MyMediaLite. To contact us, send an e-mail to

[mymedialite@ismll.de](mailto:mymedialite@ismll.de)

## Acknowledgements

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



This work was partly funded by the European Commission FP7 project MyMedia (Dynamic Personalization of Multimedia, <http://www.mymediaproject.org/>) under the grant agreement no. 215006.



# MyMediaLite – Recommender System Algorithm Library



Machine Learning Lab

December 2010

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, 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

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
		5		4
The Usual Suspects	3	4		3
American Beauty			4	
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.

