



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; factor-wise/SGD training; optimized for RMSE or MAE

Item Prediction

- random
- most popular item
- linear content-based model optimized for BPR (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

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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>



MyMediaLab's Key Features

- **Choice:**
 - Dozens of different recommendation methods (see list on this flyer),
 - methods can use collaborative, content, or relational 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 less than 200 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 models.
- **Real-time incremental 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 MyMediaLabite recommenders as baseline methods in benchmarks.
 - Use MyMediaLabite'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 MyMediaLabite 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
		5		4
The Usual Suspects	3	4		3
American Beauty		??		1
The Godfather		2		
Road Trip				

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.

