

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/

Get/branch the source code:

http://gitorious.org/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

October 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/



Recommendation Tasks Addressed

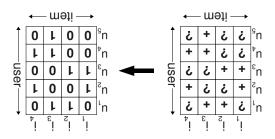
Rating Prediction

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 I to 5, the goal is predict unknown ratings.

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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 positiveonly, i.e. we know users like the products they 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.





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.

Students

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

Dynamic Personalization of Multimedia

MyMediaLite's Key Features

- Choice:
- Dozens of different recommender engines (see list on this flyer),
- methods can use collaborative and attribute/content data.
- Serialization: save and reload recommender engine models.
- Real-time online updates for most models.
- 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.
- **Portability:** Written in C#, for the .NET platform; runs on every architecture where Mono works: Linux, Windows, Mac OS X.

Compactness: Core library is 85KB "big".

• Freedom: Free/Open Source software, distributed under the terms of the GNU General Public License (GPL).