



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
 - using collaborative or attribute (content) data
 - different similarity measures
- (Biased) matrix factorization

Item Prediction

- Random
- Most Popular Item
- Linear Content-based Model Optimized for Bayesian Personalized Ranking (BPR-Linear)
- Singular Value Decomposition (SVD)
- k-Nearest Neighbor (kNN):
 - based on user or item similarities
 - using collaborative or attribute (content) data
- Weighted Regularized Matrix Factorization (WR-MF)
- Matrix Factorization Optimized for Bayesian Personalized Ranking (BPR-MF)



Download

Get the code here:

<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

Pre-release at ACM RecSys in Barcelona

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://gitorious.org/mymedialite>



Recommendation Tasks Addressed

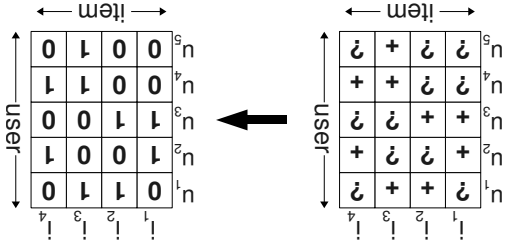
Rating Prediction

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 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 | | | | |

Item Recommendation from Implicit Feedback

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.



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 implemented.
- Use MyMediaLite as a basis for your school projects.



MyMediaLite's Features

- **Choice:** Dozens of different recommender engines (see list on this flyer), methods can use collaborative and attribute/content data,
- support for on-line updates to most models,
- **Ready to use:**

- Includes evaluation routines for rating and item prediction; quality measures MAE, RMSE, AUC, prec@N, 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
- **Freedom:** Free/Open Source software, distributed under the terms of the GNU General Public License (GPL)