Multi-purpose Library of Recommender System Algorithms for the Item Prediction Task

Presentation of my Bachelor Thesis

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Contents

Contents

Implicit Feedback

	Anna	Berta	Claudia	Dagmar
The Shawshank Redemption	1		1	
The Godfather		1	1	
The Godfather: Part II		1		1
Pulp Fiction	1	1		1
The Good, the Bad and the Ugly	1		1	

Item Prediction Task

	Anna	Berta	Claudia	Dagmar
The Shawshank Redemption	1		1	?
The Godfather		1	1	?
The Godfather: Part II		1		1
Pulp Fiction	1	1		1
The Good, the Bad and the Ugly	1		1	?

Notation

	Anna	Berta	Claudia	Dagmar
The Shawshank Redemption	1		1	
The Godfather		1	1	
The Godfather: Part II		1		1
Pulp Fiction	1	1		1
The Good, the Bad and the Ugly	1		1	

Items

Users

Interactions

Basket of u

Related Work

- **MyMediaLite** C#, several recommender algorithms
- **PREA** (Personalized Recommandation Algorithms Toolkit) Java, recommender algorithms and evaluation metrics
- **Apache Mahout** Java, machine learning on top of Apache Hadoop
- **Duine Framework** Java, combination of multiple recommender algorithms
- **Cofi** C++, centers on one recommender algorithm
- **Lenskit** Java, toolkit for recommendation and evaluation
- **Scikit-learn** Python, machine learning, no recommender algorithms

Contents

Motivation for recsyslab

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- Python for easy readable source code
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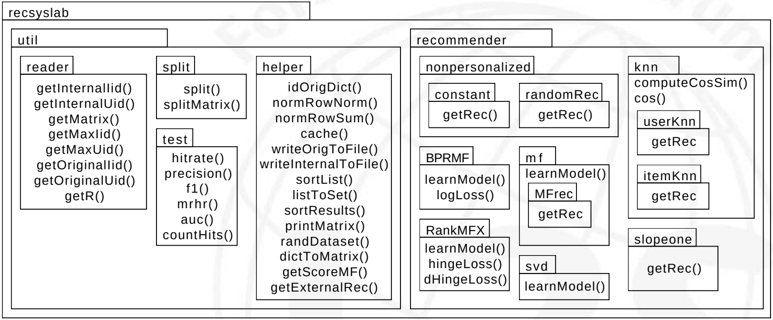
- Open source license: GPLv3

General Structure



Get recsyslab

github.com/Foolius/recsyslab

github.com/Foolius/recsyslab/archive/master.zip

```
$ git clone
    https://github.com/Foolius/recsyslab.git
```

Recommender Algorithms in recsyslab

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- Matrix Factorization [mat, 2013]
  - Bayesian Personalized Ranking (BPRMF) [Rendle et al., 2009]
  - RankMFX [Diaz-Aviles et al., 2012]
  - Ranking SVD [Jahrer and Töscher, 2011]

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  - Item-Based
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- Slope One [Lemire and Maclachlan, 2007]

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  - Ranking SVD [Jahrer and Töscher, 2011]
- k-Nearest-Neighbor[Karypis, 2001]
  - Item-Based
  - User-Based
- Slope One [Lemire and Maclachlan, 2007]
- Non-Personalized
  - Constant
  - Random

Matrix Factorization [mat, 2013]

	Anna	Berta	Claudia	Dagmar
The Shawshank Redemption	1	0	1	0
The Godfather	0	1	1	0
The Godfather: Part II	0	1	0	1
Pulp Fiction	1	1	0	1
The Good, the Bad and the Ugly	1	0	1	0

Find W and H so: $\hat{M} = W\ H^\top$.

$$\text{Score}(u, i) = W_u I_i^\top. \tag{1}$$

Matrix Factorization, Training

```
repeat until conversion of W and H:
    u=randomly chosen user
    i=randomly chosen item U interacted with
    j=randomly chosen item U did not interact
      with

    X=H[i] - H[j]
    wx=dot product of W[u] and X
    dloss=(derivative of the loss
           function of wx and 1) * learningRate

    W[u]+=dloss*(H[i] - H[j]) #These three lines
    H[i]+=dloss*W[u]          #have to be
    H[j]+=dloss*-W[u]         #executed at once
```

```
for i in xrange(0, iterations):
    u = random.choice(R.keys())
    userItems = [x[0] for x in R[u]]
    # the positive example
    i = userItems[np.random.random_integers(0, len(userItems) - 1)]
    # the negative example
    j = np.random.random_integers(0, m_items)
    # if  j is also relevant for u we continue
    # we need to see a negative example to contrast the positive one
    while j in userItems:
        j = np.random.random_integers(0, m_items)

    X = H[i] - H[j]
    wx = np.dot(W[u], X)
    dloss = dlossF(wx, y)

    # temp
    wu = W[u]
    hi = H[i]
    hj = H[j]
    if dloss != 0.0:
        # Updates
        eta_dloss = learningRate * dloss
        W[u] += eta_dloss * (hi - hj)
        H[i] += eta_dloss * wu
        H[j] += eta_dloss * (-wu)
        W[u] *= scaling_factorU
        H[i] *= scaling_factorI
        H[j] *= scaling_factorJ
```

k-Nearest-Neighbor [Karypis, 2001]

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1. Compute similarity of each (item, item) pair

$$\text{sim}(i,j) = \cos(\vec{i},\vec{j}) = \frac{\vec{i}\cdot\vec{j}}{||\vec{i}||_2||\vec{j}||_2} \tag{2}$$

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2. For each item, save the k items with the highest similarity (= neighbors)

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3. Compute the union of the neighbors of the basket of u

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2. For each item, save the k items with the highest similarity (= neighbors)
3. Compute the union of the neighbors of the basket of u
4. For each item in this set compute the sum of similarities to the basket of u
5. Sort by this score and return the first N items

k-Nearest-Neighbor [Karypis, 2001]

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$$\mathsf{sim}(i,j) = \cos(\vec{i},\vec{j}) = \frac{\vec{i}\cdot\vec{j}}{||\vec{i}||_2||\vec{j}||_2} = \frac{0}{2} = 0$$

k-Nearest-Neighbor [Karypis, 2001]

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$$\mathsf{sim}(i,j) = \cos(\vec{i},\vec{j}) = \frac{\vec{i}\cdot\vec{j}}{||\vec{i}||_2||\vec{j}||_2} = \frac{2}{\sqrt{2}\sqrt{3}}$$

Leave-one-out Protocol [lea, 2013]

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3. Get recommendations for every user
4. Compute the chosen evaluation metric with the hidden items and the recommendations

Evaluation Metrics in recsyslab

- Hitrate/Recall@N [Karypis, 2001, Sarwar et al., 2000]
- Precision [Sarwar et al., 2000]
- F1 [Sarwar et al., 2000]
- Mean Reciprocal Hitratea (MRHR) [Ning and Karypis, 2011]
- Area under the ROC (AUC) [Rendle et al., 2009]

Hitrate/Recall@N [Karypis, 2001, Sarwar et al., 2000]

$$\text{Recall@N} = \frac{\sum_{u \in U} H_u \cap \text{topN}_u}{|H|} \qquad (3)$$

H	hidden interactions
H_u	the hidden interaction of u
U	set of users
$topN_u$	N recommendations for u

Contents

MovieLens Dataset

- 100 000 interactions
- 943 users
- 1682 items
- Text file with columns separated with a single tab
- Provided by the GroupLens research lab

Movielens Dataset Excerpt

user	item	rating	time stamp
196	242	3	881250949
186	302	3	891717742
22	377	1	878887116
244	51	2	880606923
166	346	1	886397596
298	474	4	884182806
115	265	2	881171488
253	465	5	891628467
305	451	3	886324817
6	86	3	883603013
62	257	2	879372434
286	1014	5	879781125
200	222	5	876042340

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Outlook

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- More algorithms

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- More algorithms
- Refine hyperparameters with more experiments
- Update function for the models
- Incorporate user feedback about the library

Conclusions

- Python for easy readable source code
- Simple to use
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Have Fun!

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(2013).
The leave-one-out protocol.
http://en.wikipedia.org/wiki/Cross-validation_%28statistics%29#Leave-one-out_cross-validation.

(2013).
Matrix factorization.
http://en.wikipedia.org/wiki/Matrix_factorization.

Diaz-Aviles, E., Drumond, L., Gantner, Z., Schmidt-Thieme, L., and Nejdl, W. (2012).
What is happening right now... that interests me?: online topic discovery and recommendation in twitter.
In *Proceedings of the 21st ACM international conference on Information and knowledge management*, pages 1592–1596. ACM.

- Jahrer, M. and Töscher, A. (2011).
  Collaborative filtering ensemble for ranking.
  In *Proc. of KDD Cup Workshop at 17th ACM SIGKDD Int. Conf. on Knowledge Discovery and Data Mining, KDD*, volume 11.

- Karypis, G. (2001).
  Evaluation of item-based top-n recommendation algorithms.
  In *Proceedings of the tenth international conference on Information and knowledge management*, CIKM '01, pages 247–254, New York, NY, USA. ACM.

- Lemire, D. and Maclachlan, A. (2007).
  Slope one predictors for online rating-based collaborative filtering.
  CoRR, abs/cs/0702144.

Ning, X. and Karypis, G. (2011).
Slim: Sparse linear methods for top-n recommender systems.
In Cook, D. J., Pei, J., Wang, W., Zaïane, O. R., and Wu, X., editors, *ICDM*, pages 497–506. IEEE.

Rendle, S., Freudenthaler, C., Gantner, Z., and Schmidt-Thieme, L. (2009).
Bpr: Bayesian personalized ranking from implicit feedback.
In *Proceedings of the Twenty-Fifth Conference on Uncertainty in Artificial Intelligence*, UAI '09, pages 452–461, Arlington, Virginia, United States. AUAI Press.

Sarwar, B. M., Karypis, G., Konstan, J. A., and Riedl, J. T. (2000).
Application of dimensionality reduction in recommender system – a case study.

In *IN ACM WEBKDD WORKSHOP*.