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

Presentation of my Bachelor Thesis

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Demonstration of recsyslab

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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

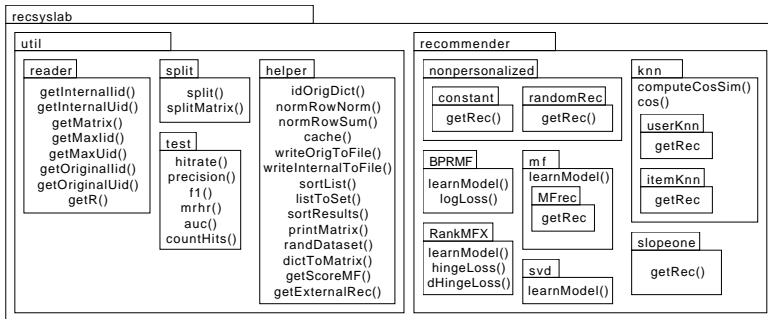# Motivation for recsyslab

▶ Python for easy readable source code

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Motivation for recsyslab

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

General Structure

recsyslab

util

reader
getInternalIid()
getInternalUid()
getMatrix()
getMaxIid()
getMaxUid()
getOriginalIid()
getOriginalUid()
getR()

split
split()
splitMatrix()

test
hitrate()
precision()
f1()
mrhr()
auc()
countHits()

helper
idOrigDict()
normRowNorm()
normRowSum()
cache()
writeOrigToFile()
writeInternalToFile()
sortList()
listToSet()
sortResults()
printMatrix()
randDataset()
dictToMatrix()
getScoreMF()
getExternalRec()

recommender

nonpersonalized

constant
getRec()

randomRec
getRec()

BPRMF
learnModel()
logLoss()

RankMFX
learnModel()
hingeLoss()
dHingeLoss()

mf
learnModel()

MFrec
getRec()

svd
learnModel()

knn
computeCosSim()
cos()

userKnn
getRec

itemKnn
getRec

slopeone
getRec()

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

Recommender Algorithms in recsyslab

- ▶ 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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- ▶ k-Nearest-Neighbor[Karypis, 2001]
  - ▶ Item-Based
  - ▶ User-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: $\hat{M} = W H^{\top}$.

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

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

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

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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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5. Sort by this score and return the first N items

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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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The Good, the Bad and the Ugly	1	0	1	0

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

Leave-one-out Protocol [lea, 2013]

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1. Randomly choose one interaction per user and hide them

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Leave-one-out Protocol [lea, 2013]

1. Randomly choose one interaction per user and hide them
2. Train the recommender system with the remaining interactions
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]

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

H hidden interactions

H_u the hidden interaction of u

U set of users

$topN_u$ N recommendations for u

Contents

MovieLens Data Set

- ▶ 100 000 interactions
- ▶ 943 users
- ▶ 1682 items
- ▶ Text file with columns separated with a single tab

Movielens Data Set 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

Contents

Outlook

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- ▶ More algorithms

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Outlook

- ▶ 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
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- ▶ Open source license: GPLv3

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Have Fun!

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```

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