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FISM: Factored Item Similarity Models for Top-N Recommender Systems

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Outline

- Background
- Motivation
- FISM
  - Basic FISM
  - FISMrmse
  - FISMauc
- Evaluation
- Conclusion

What is recommender system?

Information Overload

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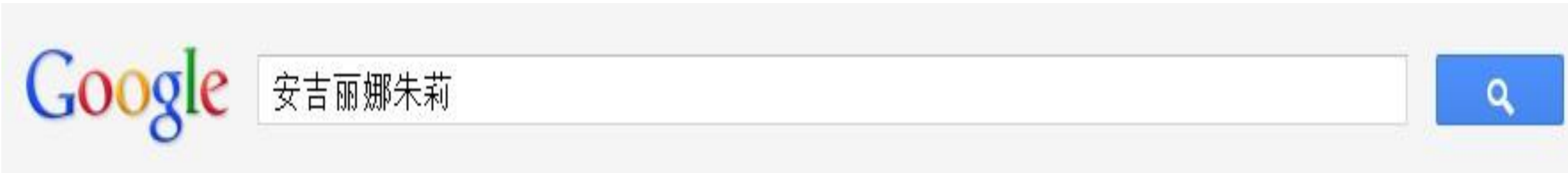

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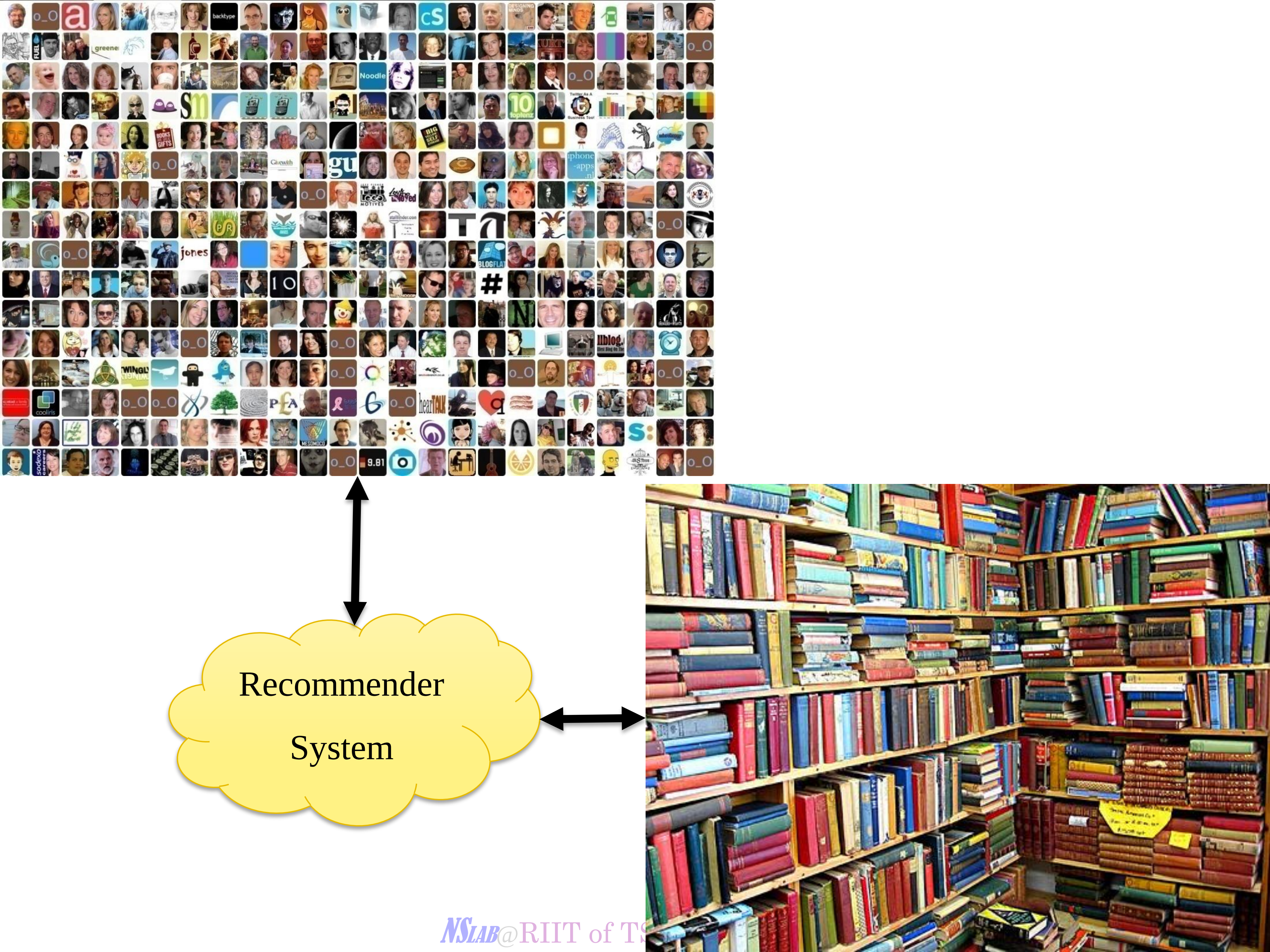
Search Engine VS. Recommender System

- User will try search engine if
  - they have specific needs
  - they can use keywords to describe needs
- User will try recommender system if
  - they do not know what they want now
  - they can not use keywords to describe needs

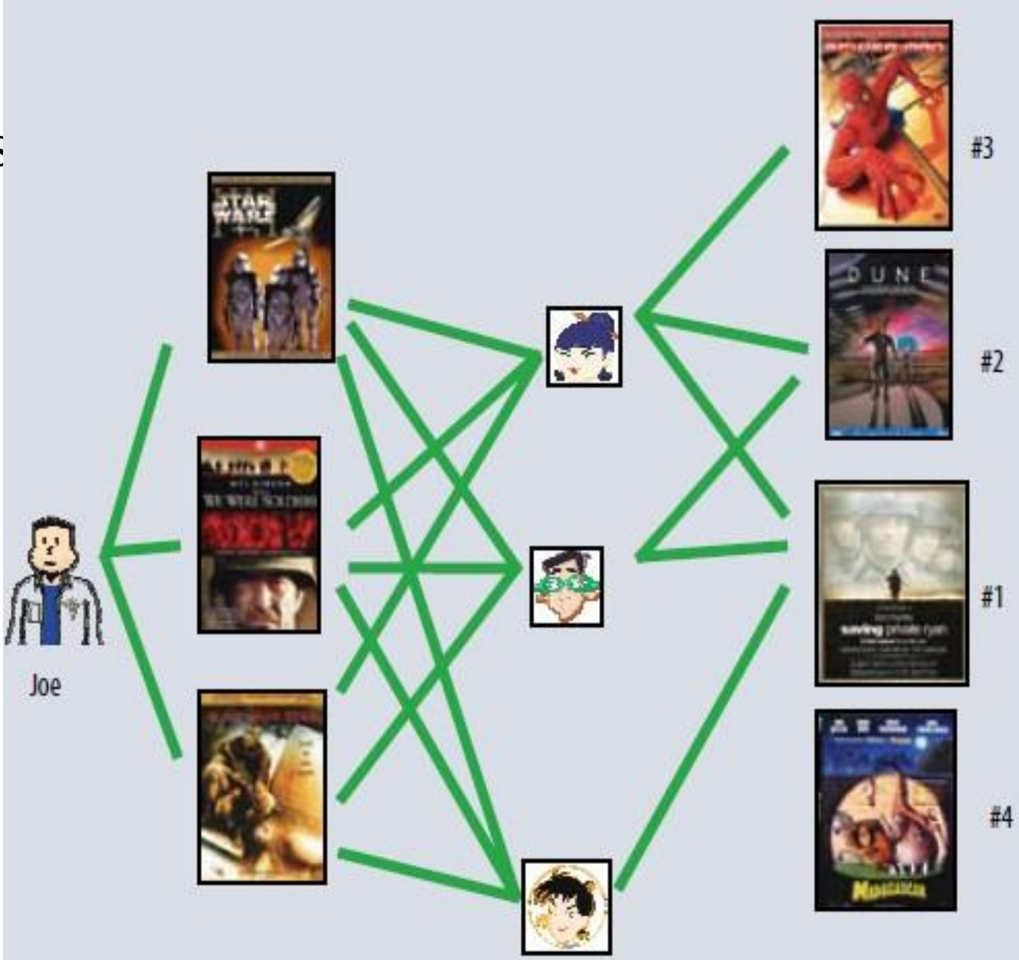
Mission

- Help user find item of their interest
- Help item provider deliver their item to right user
- Help website improve user's loyalty


Recommender
System

Background

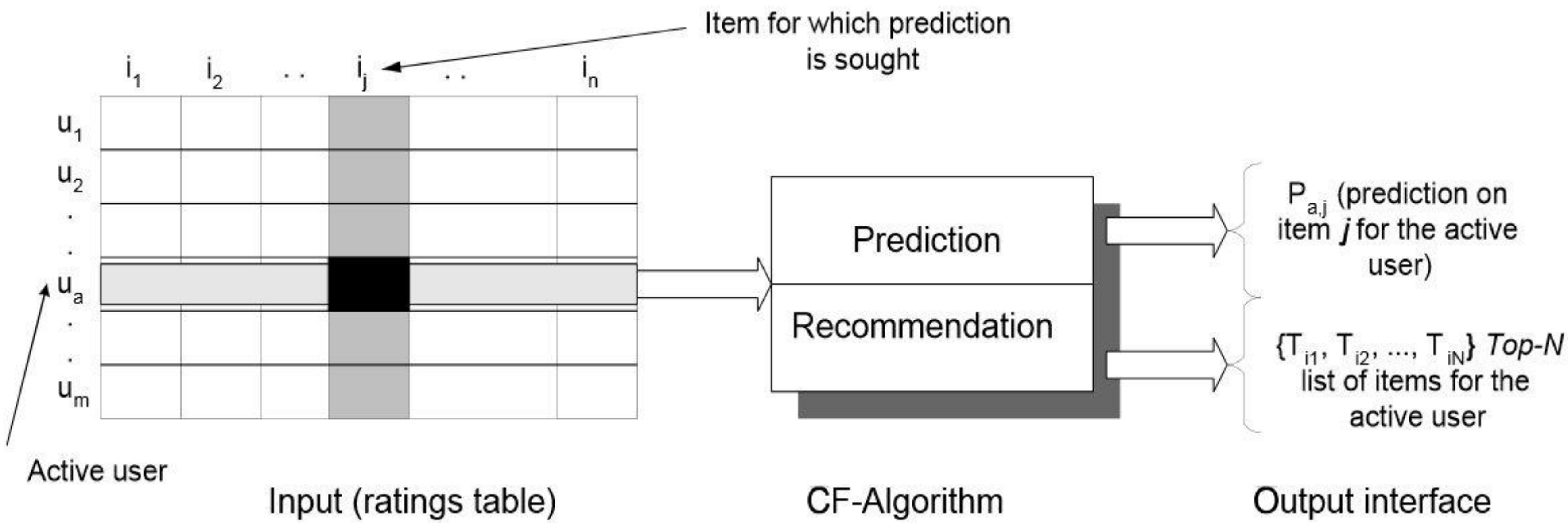
- Content filtering
  - Music Genome Project (Pandora.com)
- Collaborative filtering
  - Neighborhood methods
    - User based
    - Item based
  - Latent factor models



Collaborative Filtering

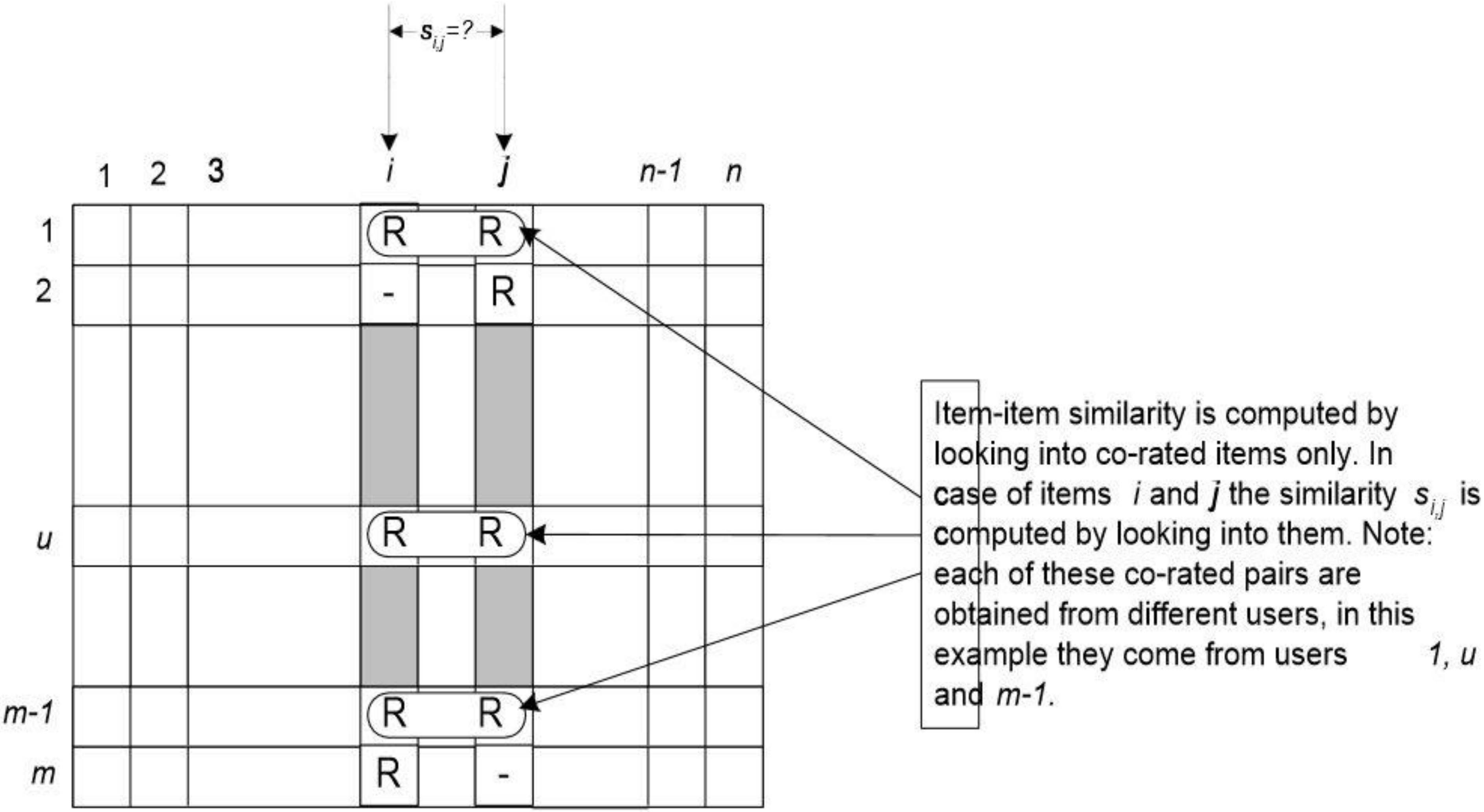
- User based
  - Users with similar history selections will share same future interest
- Item based
  - Users will like items similar to what they consumed before

The Process

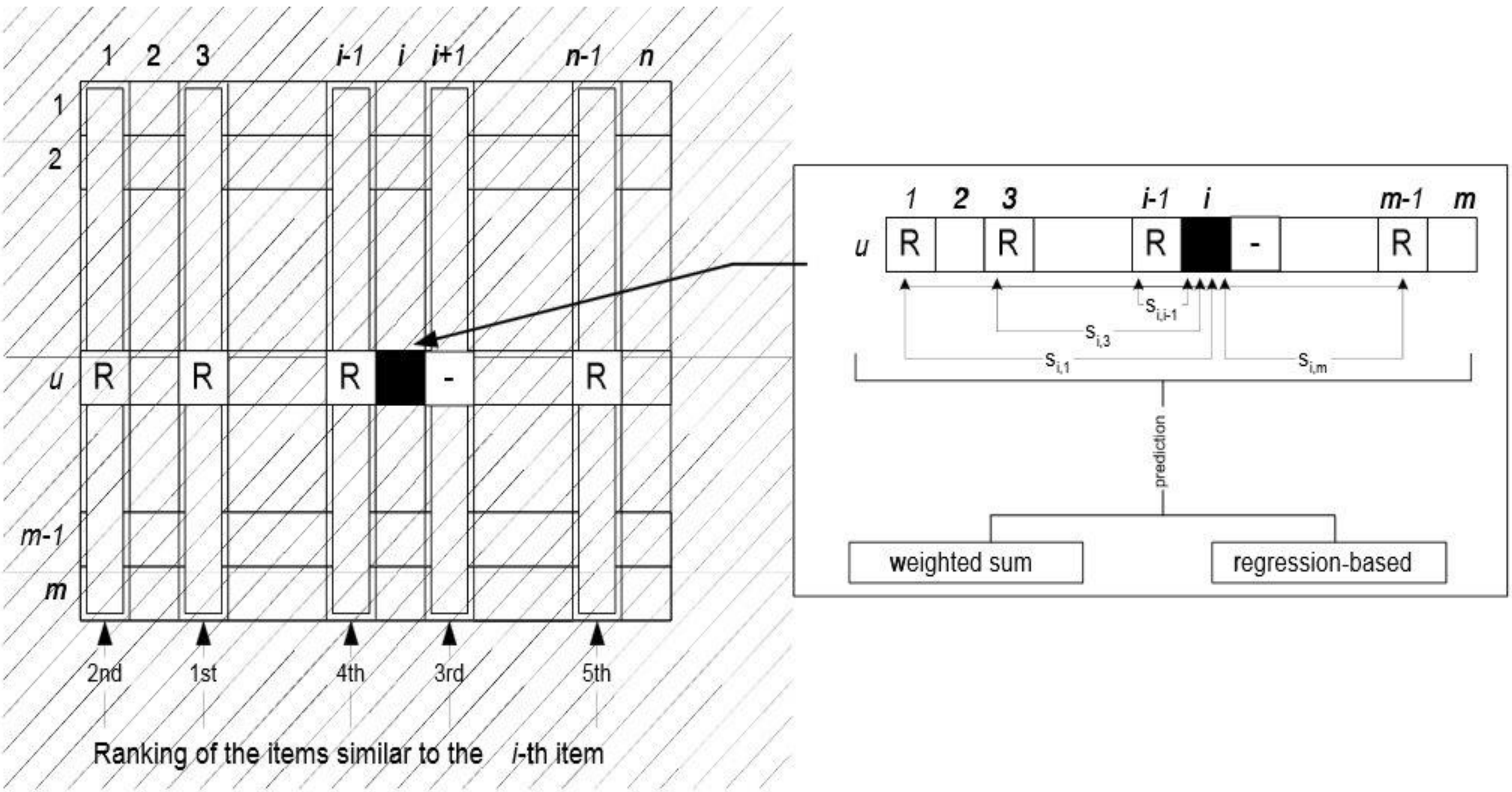


Item for which prediction is sought
i_1 i_2 . . i_j . . i_n
u_1
u_2
u_a
u_m
Active user
Input (ratings table)
Prediction
Recommendation
CF-Algorithm
$P_{a,j}$ (prediction on item *j* for the active user)
$\{T_{i1}, T_{i2}, ..., T_{iN}\}$ *Top-N* list of items for the active user
Output interface

Item based CF



Item based CF



SLIM

$$\tilde{\mathbf{r}}_u = \mathbf{r}_u \mathbf{S}$$

where $\mathbf{r}_u$ is the rating vector of u on all items and $\mathbf{S}$ is a $m \times m$ sparse matrix of aggregation coefficients.

$$\underset{\mathbf{S}}{\text{minimize}} \ \frac{1}{2}\|\mathbf{R} - \mathbf{R}\mathbf{S}\|_F^2 + \frac{\beta}{2}\|\mathbf{S}\|_F^2 + \lambda\|\mathbf{S}\|_1$$

$$\text{subject to} \ \mathbf{S} \geq 0\,, \ \ \text{diag}(\mathbf{S}) = 0,$$

NSVD

In this method, an item-item similarity was learned as a product of two low-rank matrices, $\mathbf{P}$ and $\mathbf{Q}$, where $\mathbf{P} \in \mathbb{R}^{m \times k}$, $\mathbf{Q} \in \mathbb{R}^{m \times k}$, and $k \ll m$.

$$\tilde{r}_{ui} = b_u + b_i + \sum_{j \in \mathcal{R}_u^+} \mathbf{p}_j \mathbf{q}_i^{\mathsf{T}}$$

where b_u and b_i are the user and item biases and $\mathcal{R}_u^+$ is the set of items rated by u. The parameters of this model are estimated as the minimizer to the following optimization problem:

$$\underset{\mathbf{P},\mathbf{Q}}{\text{minimize}} \ \frac{1}{2} \sum_{u \in \mathcal{C}} \sum_{i \in \mathcal{R}_u^+} \| r_{ui} - \hat{r}_{ui} \|_F^2 + \frac{\beta}{2} (\|\mathbf{P}\|_F^2 + \|\mathbf{Q}\|_F^2)$$

Motivation

- Sparse user-item rating matrix results in Item based and SLIM, which rely on learning similarities between items, fail to capture the dependencies between items that have not been co-rated by at least one user.
- Methods based on matrix factorization, alleviate this problem by projecting the data onto a low dimensional space, thereby implicitly learning better relationships between the users and items (including items which are not co-rated). However, such methods are consistently out-performed by SLIM
- NSVD does not exclude the diagonal entries while estimating the ratings during learning and prediction phases. In this case it can lead to rather trivial estimates, in which an item ends up recommending itself.

Basic FISM

Estimated value

$$\tilde{r}_{ui} = b_u + b_i + (n_u^+)^{-\alpha} \sum_{j \in \mathcal{R}_u^+} \mathbf{p}_j \mathbf{q}_i^\mathsf{T}$$

where $\mathcal{R}_u^+$ is the set of items rated by user u, $\mathbf{p}_j$ and $\mathbf{q}_i$ are the learned item latent factors, n_u^+ is the number of items rated by u, and α is a user specified parameter between 0 and 1.

FISMrmse

Loss function: RMSE

$$\mathcal{L}(\cdot) = \sum_{i \in \mathcal{D}} \sum_{u \in \mathcal{C}} (r_{ui} - \hat{r}_{ui})^2$$

Estimated value

$$\hat{r}_{ui} = b_u + b_i + (n_u^+ - 1)^{-\alpha} \sum_{j \in \mathcal{R}_u^+ \setminus \{i\}} \mathbf{p}_j \mathbf{q}_i^\mathsf{T}$$

Regularized optimization problem

$$\underset{\mathbf{P},\mathbf{Q}}{\text{minimize}} \ \frac{1}{2} \sum_{u,i \in R} \|r_{ui} - \hat{r}_{ui}\|_F^2 + \frac{\beta}{2}(\|\mathbf{P}\|_F^2 + \|\mathbf{Q}\|_F^2) + \frac{\lambda}{2}\|\mathbf{b_u}\|_2^2 + \frac{\gamma}{2}\|\mathbf{b_i}\|_2^2$$

Algorithm 1 FISMrmse:Learn.

procedure FISMrmse_Learn
  $\eta \leftarrow$ learning rate
  $\beta \leftarrow \ell_F$ regularization weight
  $\rho \leftarrow$ sample factor
  $iter \leftarrow 0$
  Init $\mathbf{P}$ and $\mathbf{Q}$ with random values in (-0.001, 0.001)

  while $iter < maxIter$ or error on validation set decreases **do**
    $\mathcal{R}' \leftarrow \mathbf{R} \cup$ *SampleZeros*$(\mathbf{R}, \rho)$
    $\mathcal{R}' \leftarrow$ *RandomShuffle*$(\mathcal{R}')$

    for all $r_{ui} \in \mathcal{R}'$ **do**
      $\mathbf{x} \leftarrow (n_u^+ - 1)^{-\alpha} \sum_{j \in \mathcal{R}_u^+ \setminus \{i\}} \mathbf{p}_j$

      $\tilde{r}_{ui} \leftarrow b_u + b_i + \mathbf{q}_i^{\mathsf{T}} \mathbf{x}$
      $e_{ui} \leftarrow r_{ui} - \tilde{r}_{ui}$
      $b_u \leftarrow b_u + \eta \cdot (e_{ui} - \lambda \cdot b_u)$
      $b_i \leftarrow b_i + \eta \cdot (e_{ui} - \gamma \cdot b_i)$
      $\mathbf{q}_i \leftarrow \mathbf{q}_i + \eta \cdot (e_{ui} \cdot \mathbf{x} - \beta \cdot \mathbf{q}_i)$

      for all $j \in \mathcal{R}_u^+ \setminus \{i\}$ **do**
        $\mathbf{p}_j \leftarrow \mathbf{p}_j + \eta \cdot (e_{ui} \cdot (n_u^+ - 1)^{-\alpha} \cdot \mathbf{q}_i - \beta \cdot \mathbf{p}_j)$
      end for
    end for
    $iter \leftarrow iter + 1$
  end while

  return $\mathbf{P}, \mathbf{Q}$
end procedure

FISMauc

Loss function: AUC

Given user's rated items in $\mathcal{R}_u^+$ and unrated items in $\mathcal{R}_u^-$

$$\mathcal{L}(\cdot) = \sum_{u \in \mathcal{C}} \sum_{i \in \mathcal{R}_u^+, j \in \mathcal{R}_u^-} \left((r_{ui} - r_{uj}) - (\hat{r}_{ui} - \hat{r}_{uj})\right)^2$$

Estimated value

$$\hat{r}_{ui} = b_u + b_i + (n_u^+ - 1)^{-\alpha} \sum_{j \in \mathcal{R}_u^+ \setminus \{i\}} \mathbf{p}_j \mathbf{q}_i^\mathsf{T}$$

Regularized optimization problem

$$\underset{\mathbf{P},\mathbf{Q}}{\text{minimize}} \ \frac{1}{2} \sum_{u \in \mathcal{C}} \sum_{i \in \mathcal{R}_u^+, j \in \mathcal{R}_u^-} \|(r_{ui} - r_{uj}) - (\hat{r}_{ui} - \hat{r}_{uj})\|_F^2 + \frac{\beta}{2}(\|\mathbf{P}\|_F^2 + \|\mathbf{Q}\|_F^2) + \frac{\gamma}{2}(\|\mathbf{b_i}\|_2^2)$$

Algorithm 2 FISMauc:Learn.

```
procedure FISMauc_Learn
    $\eta \leftarrow$ learning rate
    $\beta \leftarrow \ell_F$ regularization weight
    $\rho \leftarrow$ number of sampled zeros
    $iter \leftarrow 0$
    Init $\mathbf{P}$ and $\mathbf{Q}$ with random values in (-0.001, 0.001)
    while $iter < maxIter$ or error on validation set decreases do
        for all $u \in \mathcal{C}$ do
            for all $i \in \mathcal{R}_u^+$ do
                $\mathbf{x} \leftarrow 0$
                $\mathbf{t} \leftarrow (n_u^+ - 1)^{-\alpha} \sum_{j \in \mathcal{R}_u^+ \setminus \{i\}} \mathbf{p}_j$
                $\mathcal{Z} \leftarrow SampleZeros(\rho)$
                for all $j \in \mathcal{Z}$ do
                    $\tilde{r}_{ui} \leftarrow b_i + \mathbf{t} \cdot \mathbf{q}_i^\mathsf{T}$
                    $\tilde{r}_{uj} \leftarrow b_j + \mathbf{t} \cdot \mathbf{q}_j^\mathsf{T}$
                    $r_{uj} \leftarrow 0$
                    $e \leftarrow (r_{ui} - r_{uj}) - (\tilde{r}_{ui} - \tilde{r}_{uj})$
                    $b_i \leftarrow b_i + \eta \cdot (e - \gamma \cdot b_i)$
                    $b_j \leftarrow b_j - \eta \cdot (e - \gamma \cdot b_j)$
                    $\mathbf{q}_i \leftarrow \mathbf{q}_i + \eta \cdot (e \cdot \mathbf{t} - \beta \cdot \mathbf{q}_i)$
                    $\mathbf{q}_j \leftarrow \mathbf{q}_j - \eta \cdot (e \cdot \mathbf{t} - \beta \cdot \mathbf{q}_j)$
                    $\mathbf{x} \leftarrow \mathbf{x} + e \cdot (\mathbf{q}_i - \mathbf{q}_j)$
                end for
            end for

            for all $j \in \mathcal{R}_u^+ \setminus \{i\}$ do
                $\mathbf{p}_j \leftarrow \mathbf{p}_j + \eta \cdot (\frac{1}{\rho} \cdot (n_u^+ - 1)^{-\alpha} \cdot \mathbf{x} - \beta \cdot \mathbf{p}_j)$
            end for
        end for

        $iter \leftarrow iter + 1$
    end while

    return $\mathbf{P}, \mathbf{Q}$
end procedure
```

Evaluation

- Data set
  - ML100K: ML100K-1, ML100K-2, ML100K-3
  - Netflix: Netflix-1, Netflix-2, Netflix-3
  - Yahoo Music: Yahoo-1, Yahoo-2, Yahoo-3
  - Only ML100K-3, Netflix-3, Yahoo-2 are used

Table 1: Datasets.

Dataset	#Users	#Items	#Ratings	Rsize	Csize	Density
ML100K-1	943	1,178	59,763	63.99	50.73	5.43%
ML100K-2	943	1,178	39,763	42.57	33.75	3.61%
ML100K-3	943	1,178	19,763	21.16	16.78	1.80%
Netflix-1	6,079	5,641	429,339	70.63	76.11	1.25%
Netflix-2	6,079	5,641	221,304	36.40	39.23	0.65%
Netflix-3	6,079	5,641	110,000	18.10	19.50	0.32%
Yahoo-1	7,558	3,951	282,075	37.32	71.39	0.94%
Yahoo-2	7,558	3,951	149,050	19.72	37.72	0.50%
Yahoo-3	7,558	3,951	75,000	9.92	18.98	0.25%

Evaluation

- Methodology
  - 5-fold Leave-One-Out-Cross-Validation (LOOCV)
- Metrics
  - HR (Hit Rate)

$$HR = \frac{\#hits}{\#users}$$

  - ARHR

$$ARHR = \frac{1}{\#users} \sum_{i=1}^{\#hits} \frac{1}{pos_i}$$

Evaluation

- Comparison Algorithms
  - ItemKNN(cos)
  - ItemKNN(cprob)
  - ItemKNN(log)
  - PursSVD
  - BPRkNN
  - BPRMF
  - SLIM
  - Basic FISM
  - FISMrmse
  - FISMauc

Experimental Results

$$\hat{r}_{ui} = b_u + b_i + (n_u^+ - 1)^{-\alpha} \sum_{j \in \mathcal{R}_u^+ \setminus \{i\}} \mathbf{p}_j \mathbf{q}_i^\mathsf{T}$$

Table 2: Performance of different bias schemes.

Scheme	**ML100K**				**Yahoo**			
	Beta	Lambda	Gamma	HR	Beta	Lambda	Gamma	HR
NoBias	8e-4	-	-	0.1281	2e-5	-	-	0.0974
UserBias	6e-4	0.1	-	0.1336	4e-5	0.1	-	0.1012
ItemBias	2e-4	-	0.01	0.1401	4e-5	-	1e-4	0.1007
User&ItemBias	6e-4	0.1	1e-4	0.1090	4e-5	0.1	1e-4	0.0977

Experimental Results

$$\hat{r}_{ui} = b_u + b_i + (n_u^+ - 1)^{-\alpha} \sum_{j \in \mathcal{R}_u^+ \setminus \{i\}} \mathbf{p}_j \mathbf{q}_i^\mathsf{T}$$

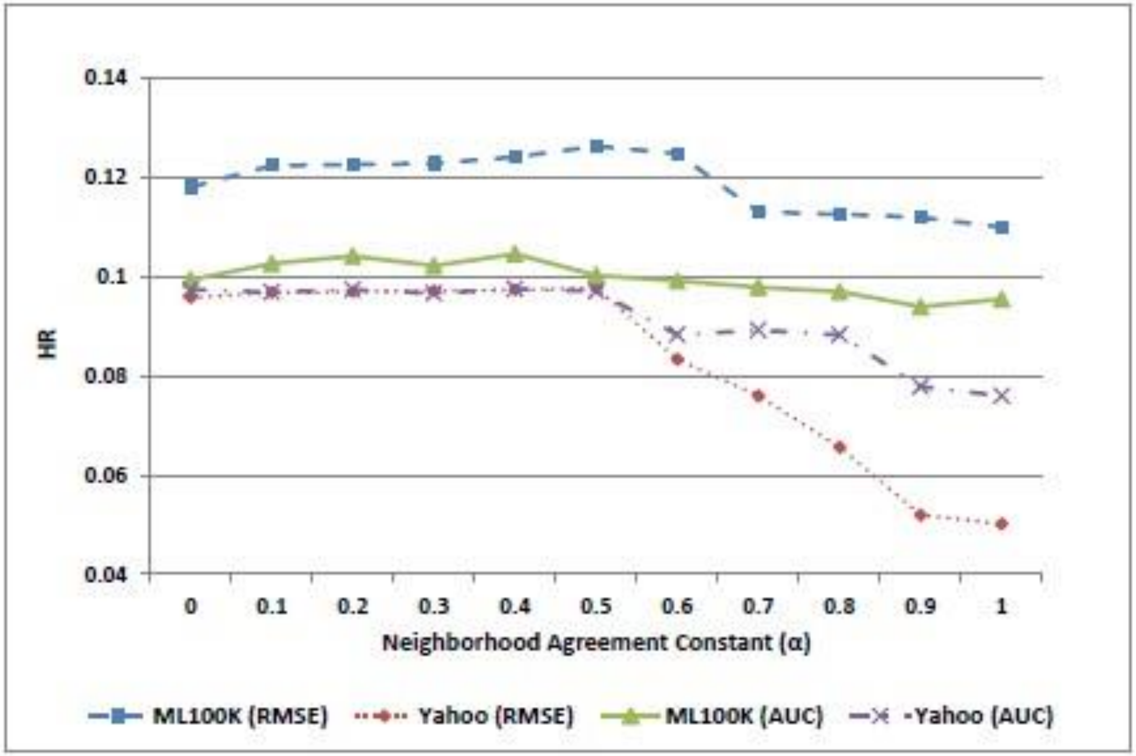


Figure 1: Effect of neighborhood agreement on performance.

Experimental Results

$$S = PQ^T$$

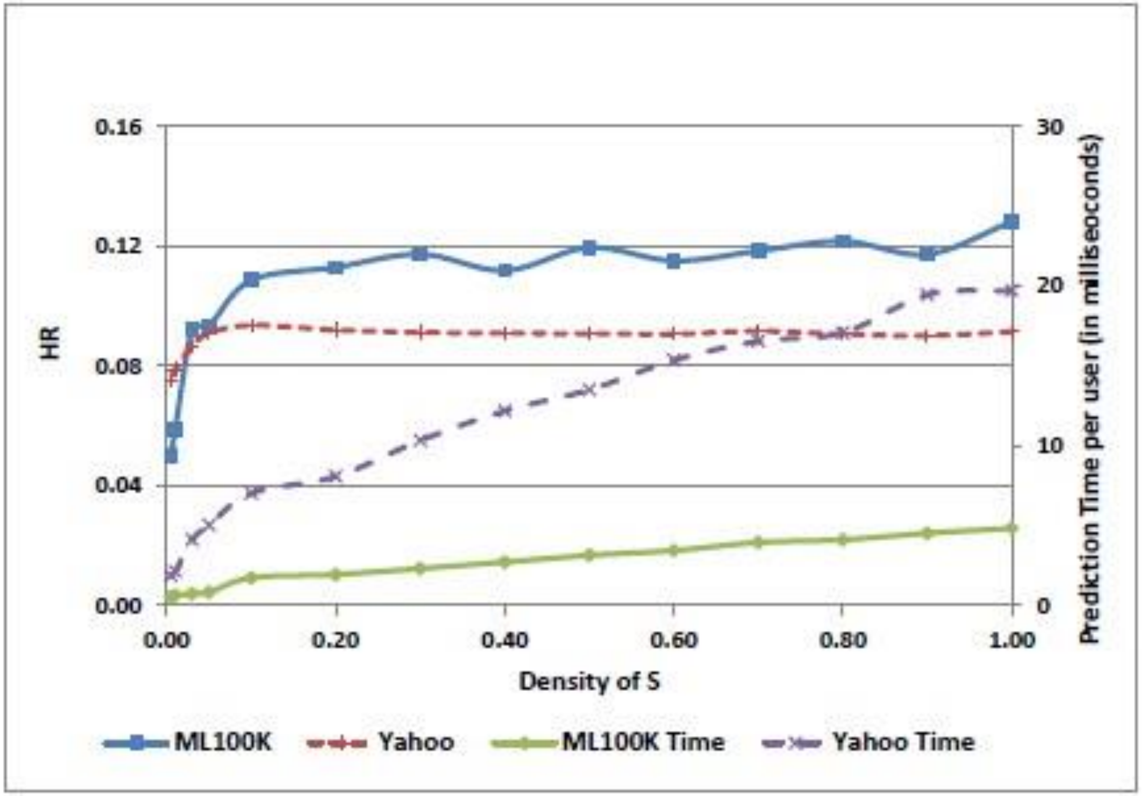
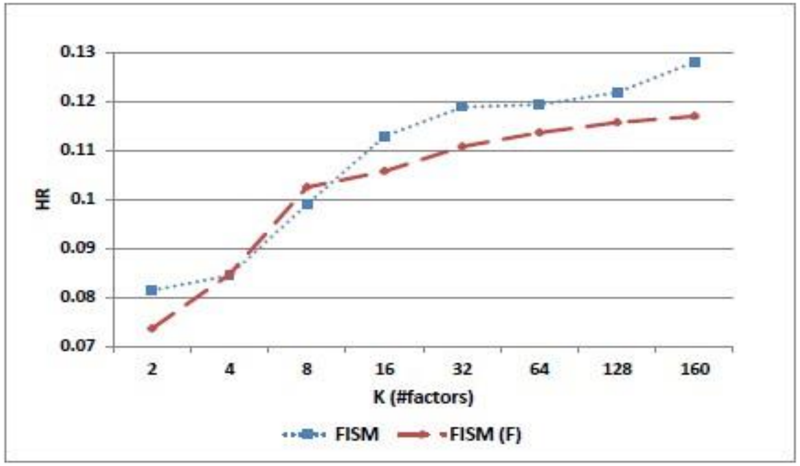
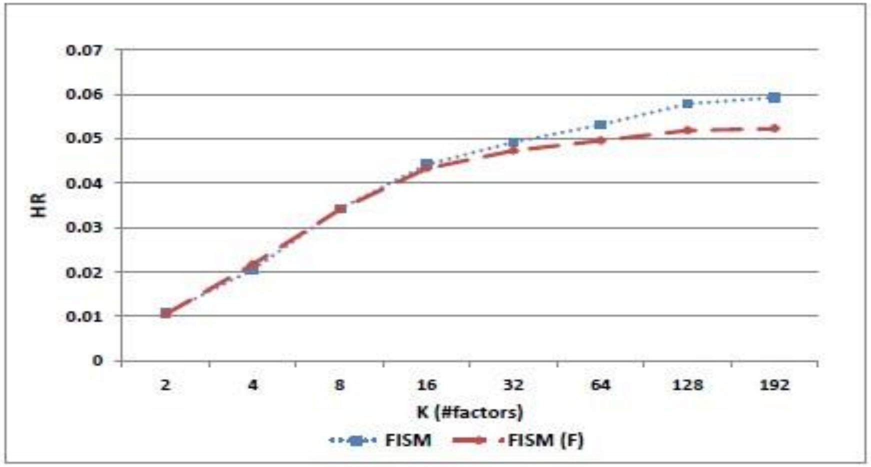


Figure 2: Performance of induced Sparsity on S.

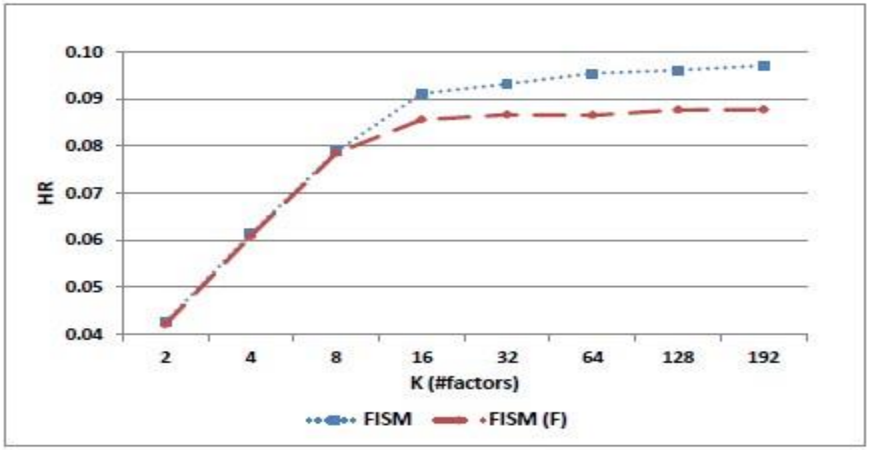
Experimental Results



(a) ML100K dataset.



(b) Netflix dataset.



(c) Yahoo dataset.

Figure 3: Effect of estimation approach on performance.

Experimental Results

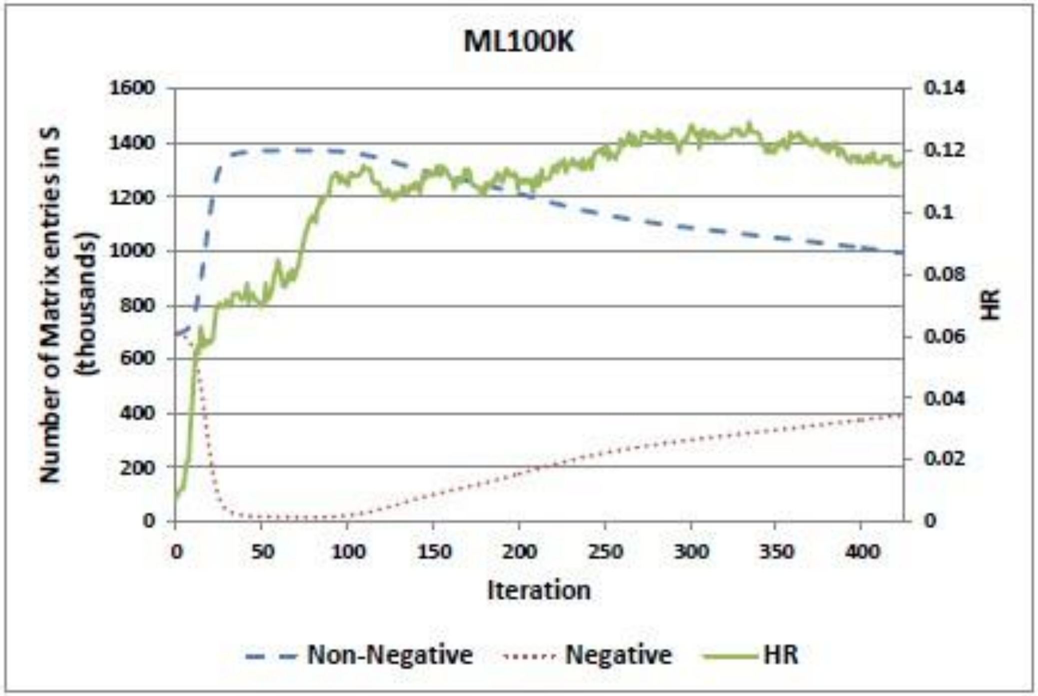
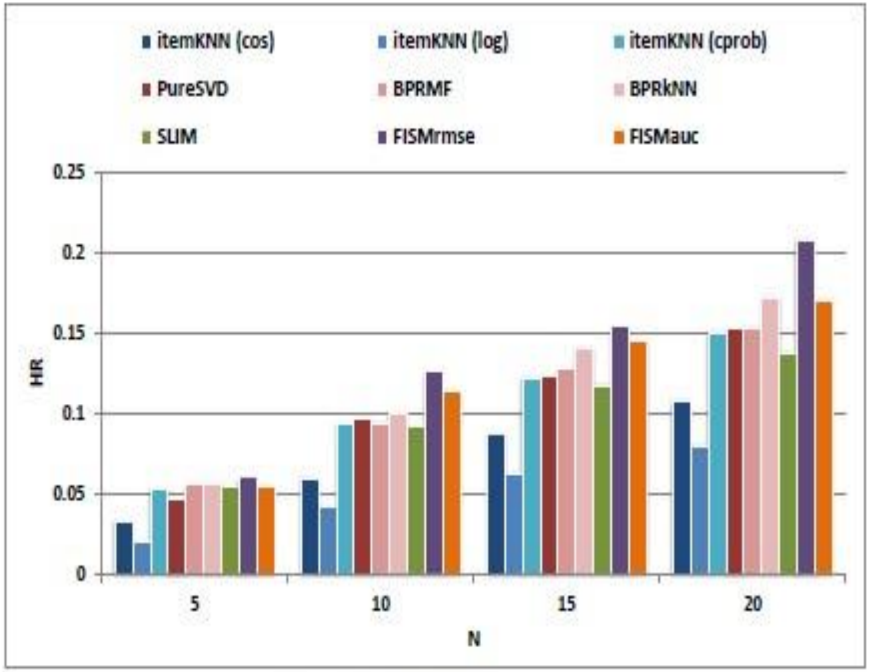
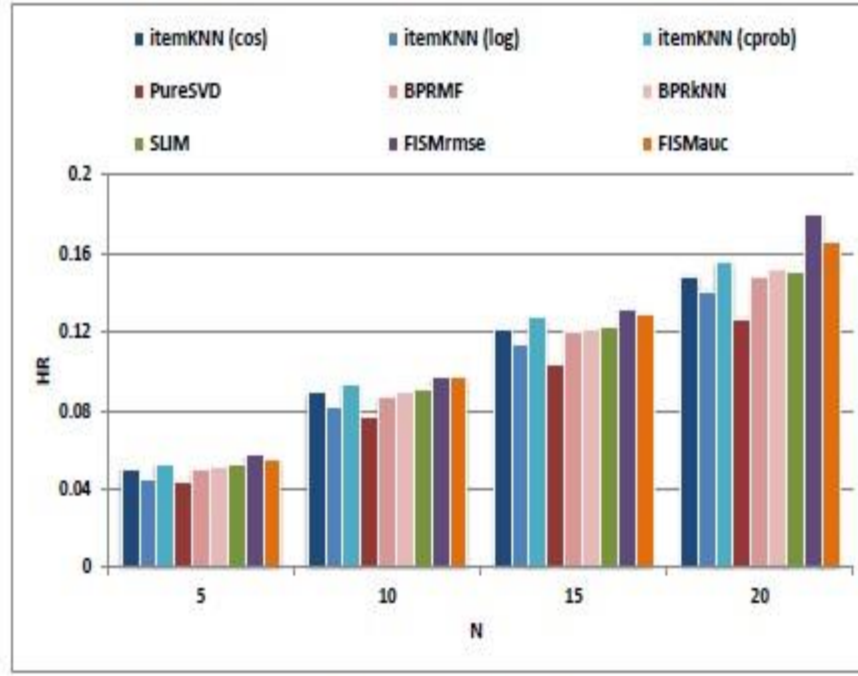


Figure 4: Non-negative and negative entries in S.

Experimental Results



(a) ML100K dataset.



(b) Yahoo dataset.

Figure 5: Performance for different values of N.

Experimental Results

Table 3: Comparison of performance of *top-N* recommendation algorithms with FISM.

Method	ML100K-1					ML100K-2					ML100K-3				
	Params			HR	ARHR	Params			HR	ARHR	Params			HR	ARHR
ItemKNN (cos)	100	-	-	0.1604	0.0578	100	-	-	0.1214	0.0393	100	-	-	0.0602	0.0193
ItemKNN (log)	100	-	-	0.1047	0.0336	100	-	-	0.0809	0.0250	100	-	-	0.0424	0.0116
ItemKNN (cprob)	500	0.6	-	0.1711	0.0581	500	0.3	-	0.1308	0.0440	400	0.1	-	0.0938	0.0293
PureSVD	10	-	-	0.1700	0.0594	10	-	-	0.1362	0.0438	5	-	-	0.0438	0.0316
BPRkNN	1e-4	0.01	-	0.1621	0.0564	1e-5	0.01	-	0.1272	0.0447	1e-5	14	-	0.1006	0.0319
BPRMF	400	0.1	-	0.1610	0.0512	700	0.1	-	0.1224	0.0407	700	0.25	-	0.0943	0.0305
SLIM	0.1	20	-	0.1782	0.0620	0.01	18	-	0.1283	0.0448	1e-4	14	-	0.0919	0.0303
FISMrmse	96	2e-5	0.001	0.1908	0.0641	64	8e-4	0.01	0.1482	0.0462	96	8e-4	0.001	0.1260	0.0384
FISMauc	64	0.001	1e-4	0.1518	0.0504	144	2e-5	5e-5	0.1304	0.0424	144	8e-5	1e-5	0.1140	0.0340

Method	Netflix-1					Netflix-2					Netflix-3				
	Params			HR	ARHR	Params			HR	ARHR	Params			HR	ARHR
ItemKNN (cos)	100	-	-	0.1516	0.0689	100	-	-	0.0849	0.0316	100	-	-	0.0374	0.0123
ItemKNN (log)	100	-	-	0.0630	0.0240	100	-	-	0.0838	0.0303	100	-	-	0.0188	0.0062
ItemKNN (cprob)	20	0.5	-	0.1555	0.0678	500	0.5	-	0.0879	0.0326	200	0.1	-	0.0461	0.0162
PureSVD	600	-	-	0.1783	0.0865	400	-	-	0.0807	0.0297	400	-	-	0.0382	0.0131
BPRkNN	1e-3	1e-4	-	0.1678	0.0781	1e-4	1	-	0.0889	0.0329	0.01	1e-3	-	0.0439	0.0148
BPRMF	800	0.1	-	0.1638	0.0719	700	0.1	-	0.0862	0.0318	5	0.01	-	0.0454	0.0153
SLIM	1e-3	8	-	0.2025	0.1008	0.1	8	-	0.0947	0.0374	1e-4	12	-	0.0422	0.0149
FISMrmse	192	2e-5	0.001	0.2118	0.1107	192	6e-5	0.001	0.1041	0.0386	128	6e-5	0.001	0.0578	0.0185
FISMauc	192	1e-5	1e-4	0.2095	0.1016	240	2e-5	1e-4	0.0979	0.0341	160	4e-4	5e-4	0.0548	0.0177

Method	Yahoo-1					Yahoo-2					Yahoo-3				
	Params			HR	ARHR	Params			HR	ARHR	Params			HR	ARHR
ItemKNN (cos)	100	-	-	0.1344	0.0502	100	-	-	0.0890	0.0295	100	-	-	0.0366	0.0116
ItemKNN (log)	100	-	-	0.1046	0.0358	100	-	-	0.0820	0.0261	100	-	-	0.0489	0.0153
ItemKNN (cprob)	500	0.6	-	0.1387	0.0510	200	0.4	-	0.0908	0.0313	20	0.1	-	0.0571	0.0187
PureSVD	50	-	-	0.1229	0.0459	20	-	-	0.0769	0.0257	20	-	-	0.0494	0.0154
BPRkNN	1e-3	1e-4	-	0.1432	0.0528	1e-3	1e-4	-	0.0894	0.0304	0.1	0.01	-	0.0549	0.0183
BPRMF	700	0.1	-	0.1337	0.0473	700	0.1	-	0.0869	0.0288	10	0.01	-	0.0530	0.0169
SLIM	0.1	12	-	0.1454	0.0542	1e-3	12	-	0.0904	0.0304	0.1	2	-	0.0491	0.0159
FISMrmse	192	1e-4	0.001	0.1522	0.0542	192	2e-5	5e-4	0.0971	0.0371	160	0.002	0.001	0.0740	0.0230
FISMauc	144	8e-5	1e-4	0.1426	0.0488	160	2e-5	5e-4	0.0974	0.0315	176	2e-4	0.001	0.0722	0.0228

Experimental Results

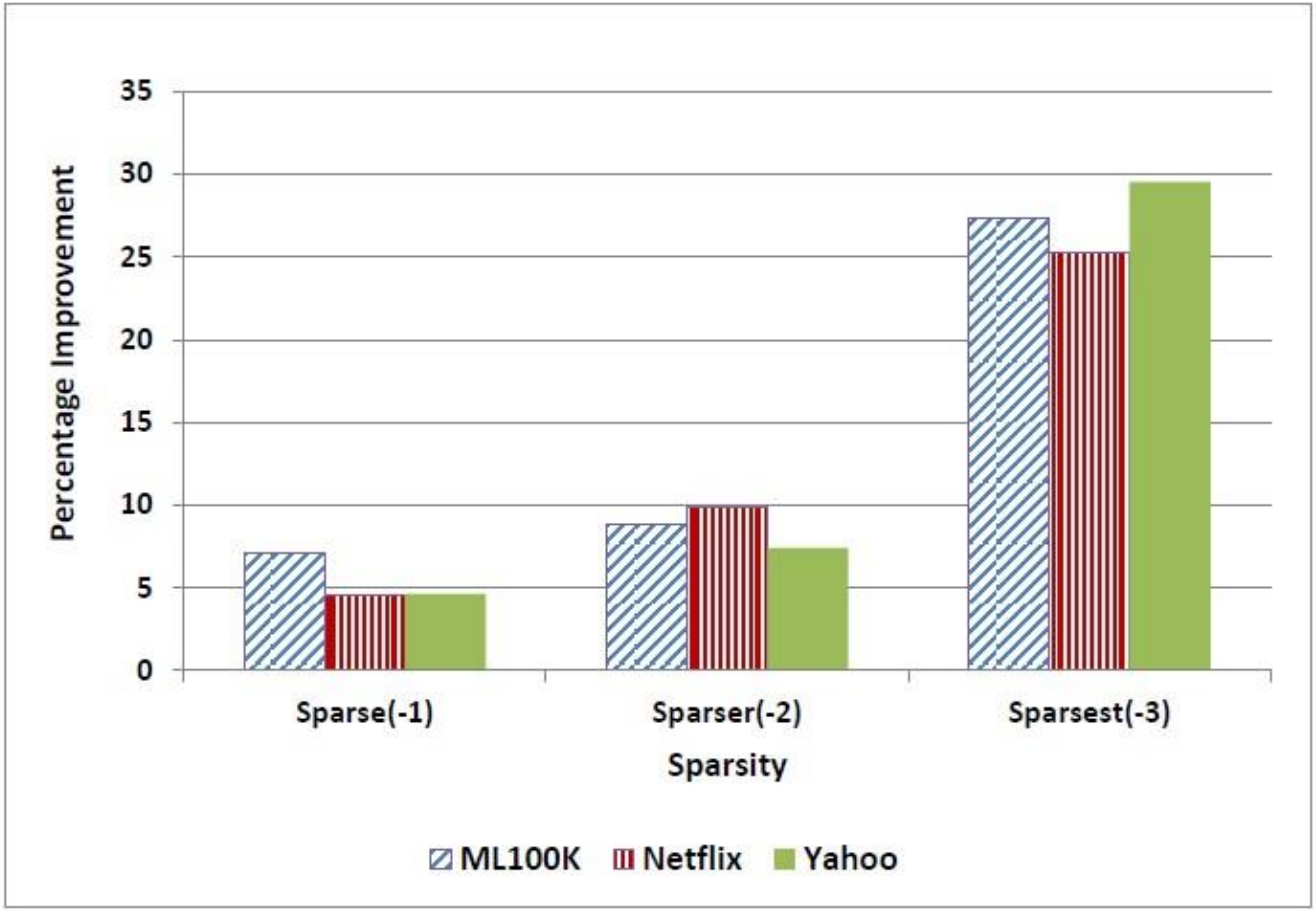


Figure 6: Effect of sparsity on performance for various datasets.

Conclusion

- This paper proposed a factored item similarity based method (FISM), which learns the item similarities as the product of two matrices.
- FISM can well cope with data sparsity problem, and better estimators are achieved as the number of factors increases.
- FISM outperforms other state-of-the-art top-N recommendation algorithms

Discussion

- Why not use RMSE as the metric?
- NSVD doesn't use unrated entries for learning, while FISM does. The comparison seems bias?
- Is there a symmetric method to factor user similarity with two low dimensional matrices?

Questions?

Thank you!