# Social Recommendation Using Probabilistic Matrix Factorization

By Hao Ma, Haixuan Yang, Michael R. Lyu, Irwin King

&

# Recommender Systems with Social Regularization

By Hao Ma, Dengyong Zhou, Chao Liu, Michael R. Lyu, Irwin King

Presented by Kim Han

# Contents - SoRec

1. Introduction
2. Background
3. Framework
4. Experiment
5. Conclusion

# Contents - SoReg

# Introduction

## Problem

**Assume that,**

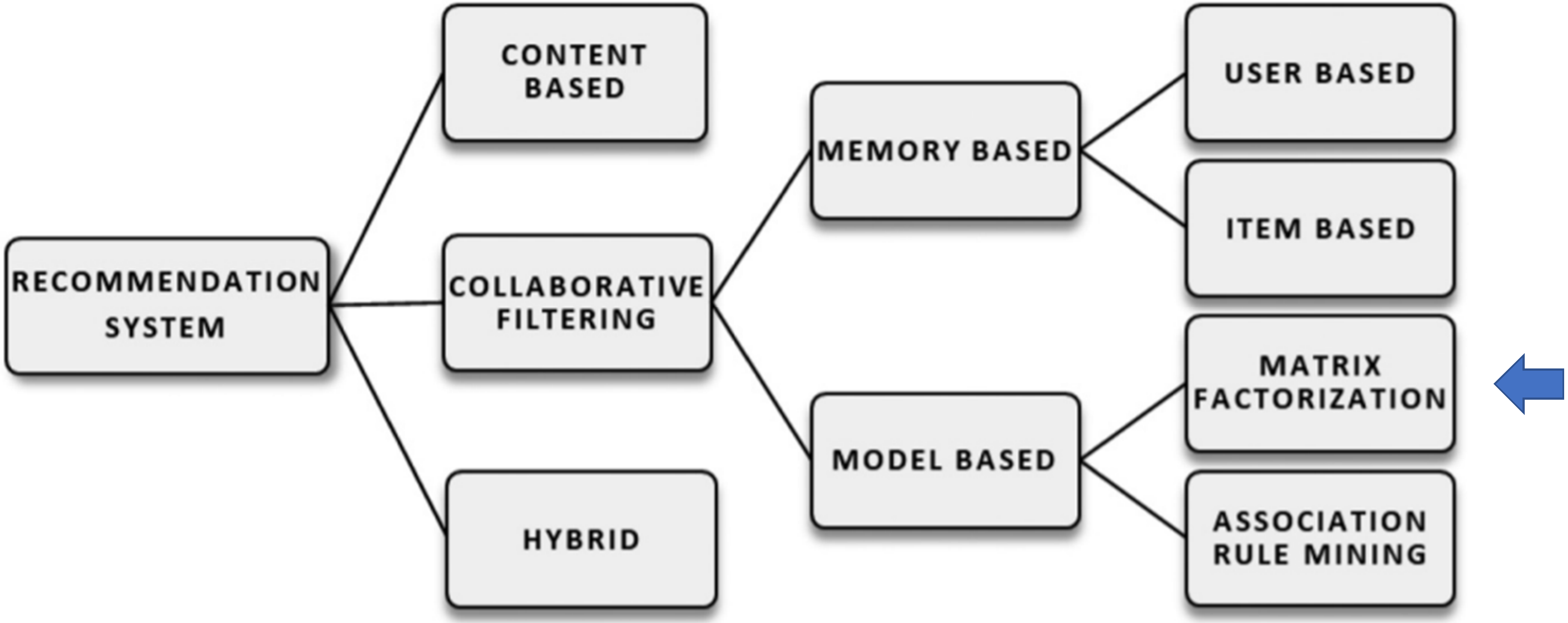
1. two users have rated at least some items in common
   → data density < 1%
2. all the users are independent and identically distributed
   → In reality, we are influenced by each other.

**Hence,**

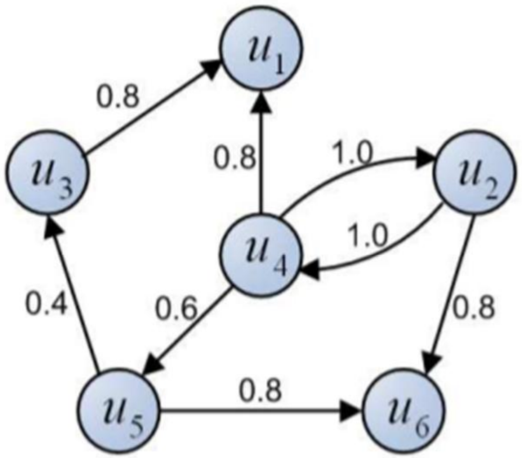
By using rating records + users' social network information,

→ 1. more accurate and 2. personal taste recommendation system.

# Background


RECOMMENDATION SYSTEM
CONTENT BASED
COLLABORATIVE FILTERING
HYBRID
MEMORY BASED
MODEL BASED
USER BASED
ITEM BASED
MATRIX FACTORIZATION
ASSOCIATION RULE MINING

# Framework




(a) Social Network Graph

→ $U^T Z$

| | $i_1$ | $i_2$ | $i_3$ | $i_4$ | $i_5$ | $i_6$ | $i_7$ | $i_8$ |
|---|---|---|---|---|---|---|---|---|
| $u_1$ | 5 | 2 | | 3 | | 4 | | |
| $u_2$ | 4 | 3 | | | 5 | | | |
| $u_3$ | 4 | | 2 | | | | 2 | 4 |
| $u_4$ | | | | | | | | |
| $u_5$ | 5 | 1 | 2 | | 4 | 3 | | |
| $u_6$ | 4 | 3 | | 2 | 4 | | 3 | 5 |

(b) User-Item Matrix

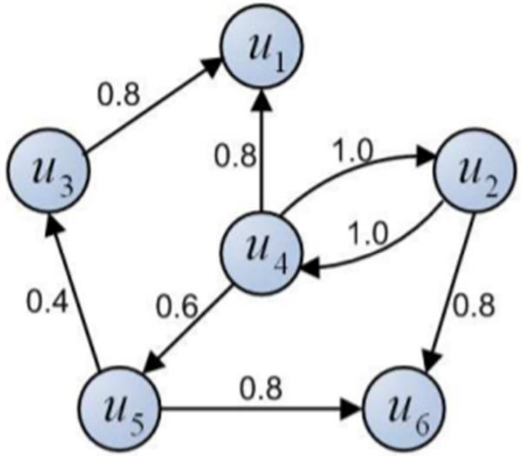
→ $U^T V$

| | $i_1$ | $i_2$ | $i_3$ | $i_4$ | $i_5$ | $i_6$ | $i_7$ | $i_8$ |
|---|---|---|---|---|---|---|---|---|
| $u_1$ | 5 | 2 | **2.5** | 3 | **4.8** | 4 | **2.2** | **4.8** |
| $u_2$ | 4 | 3 | **2.4** | **2.9** | 5 | **4.1** | **2.6** | **4.7** |
| $u_3$ | 4 | **1.7** | 2 | **3.2** | **3.9** | **3.0** | 2 | 4 |
| $u_4$ | **4.8** | **2.1** | **2.7** | **2.6** | **4.7** | **3.8** | **2.4** | **4.9** |
| $u_5$ | 5 | 1 | 2 | **3.4** | 4 | 3 | **1.5** | **4.6** |
| $u_6$ | 4 | 3 | **2.9** | 2 | 4 | **3.4** | 3 | 5 |

(c) Predicted User-Item Matrix

U - low-dimensional user latent feature space
Z - factor matrix in the social network graph
V - low-dimensional item latent feature space

# Framework




(a) Social Network Graph

| | $i_1$ | $i_2$ | $i_3$ | $i_4$ | $i_5$ | $i_6$ | $i_7$ | $i_8$ |
|---|---|---|---|---|---|---|---|---|
| $u_1$ | 5 | 2 | | 3 | | 4 | | |
| $u_2$ | 4 | 3 | | | 5 | | | |
| $u_3$ | 4 | | 2 | | | | 2 | 4 |
| $u_4$ | | | | | | | | |
| $u_5$ | 5 | 1 | 2 | | 4 | 3 | | |
| $u_6$ | 4 | 3 | | 2 | 4 | | 3 | 5 |

(b) User-Item Matrix

| | $i_1$ | $i_2$ | $i_3$ | $i_4$ | $i_5$ | $i_6$ | $i_7$ | $i_8$ |
|---|---|---|---|---|---|---|---|---|
| $u_1$ | 5 | 2 | **2.5** | 3 | **4.8** | 4 | **2.2** | **4.8** |
| $u_2$ | 4 | 3 | **2.4** | **2.9** | 5 | **4.1** | **2.6** | **4.7** |
| $u_3$ | 4 | **1.7** | 2 | **3.2** | **3.9** | **3.0** | 2 | 4 |
| $u_4$ | **4.8** | **2.1** | **2.7** | **2.6** | **4.7** | **3.8** | **2.4** | **4.9** |
| $u_5$ | 5 | 1 | 2 | **3.4** | 4 | 3 | **1.5** | **4.6** |
| $u_6$ | 4 | 3 | **2.9** | 2 | 4 | **3.4** | 3 | 5 |

(c) Predicted User-Item Matrix

$$U = \begin{bmatrix} 1.55 & 1.22 & 0.37 & 0.81 & 0.62 & -0.01 \\ 0.36 & 0.91 & 1.21 & 0.39 & 1.10 & 0.25 \\ 0.59 & 0.20 & 0.14 & 0.83 & 0.27 & 1.51 \\ 0.39 & 1.33 & -0.43 & 0.70 & -0.90 & 0.68 \\ 1.05 & 0.11 & 0.17 & 1.18 & 1.81 & 0.40 \end{bmatrix}$$

$$V = \begin{bmatrix} 1.00 & -0.05 & -0.24 & 0.26 & 1.28 & 0.54 & -0.31 & 0.52 \\ 0.19 & -0.86 & -0.72 & 0.05 & 0.68 & 0.02 & -0.61 & 0.70 \\ 0.49 & 0.09 & -0.05 & -0.62 & 0.12 & 0.08 & 0.02 & 1.60 \\ -0.40 & 0.70 & 0.27 & -0.27 & 0.99 & 0.44 & 0.39 & 0.74 \\ 1.49 & -1.00 & 0.06 & 0.05 & 0.23 & 0.01 & -0.36 & 0.80 \end{bmatrix}$$

# Framework

G = (V, E)

V = $\{v_i\}_{i=1}^{m}$

C = $\{c_{ik}\}$ $\quad c_{ik} \in (0,1]$

$$p(C|U,Z,\sigma_C^2) = \prod_{i=1}^{m}\prod_{k=1}^{m}\mathcal{N}\left[\left(c_{ik}|g(U_i^T Z_k),\sigma_C^2\right)\right]^{I_{ik}^C}$$

$$p(U|\sigma_U^2) = \prod_{i=1}^{m}\mathcal{N}(U_i|0,\sigma_U^2\mathbf{I})$$

$$p(Z|\sigma_Z^2) = \prod_{k=1}^{m}\mathcal{N}(Z_k|0,\sigma_Z^2\mathbf{I})$$

$$\begin{aligned} & p(U,Z|C,\sigma_C^2,\sigma_U^2,\sigma_Z^2) \\ & \quad \propto \quad p(C|U,Z,\sigma_C^2)p(U|\sigma_U^2)p(Z|\sigma_Z^2) \\ & \quad = \quad \prod_{i=1}^{m}\prod_{k=1}^{m}\mathcal{N}\left[\left(c_{ik}|g(U_i^T Z_k),\sigma_C^2\right)\right]^{I_{ik}^C} \\ & \quad \times \quad \prod_{i=1}^{m}\mathcal{N}(U_i|0,\sigma_U^2\mathbf{I}) \times \prod_{k=1}^{m}\mathcal{N}(Z_k|0,\sigma_Z^2\mathbf{I}) \end{aligned}$$

# Framework

$$c_{ik}^* = \sqrt{\frac{d^-(v_k)}{d^+(v_i) + d^-(v_k)}} \times c_{ik}$$

$$p(C|U, Z, \sigma_C^2) = \prod_{i=1}^{m} \prod_{k=1}^{m} \mathcal{N}\left[\left(c_{ik}|g(U_i^T Z_k), \sigma_C^2\right)\right]^{I_{ik}^C}$$

$$\Downarrow$$

$$p(C|U, Z, \sigma_C^2) = \prod_{i=1}^{m} \prod_{j=1}^{n} \mathcal{N}\left[\left(c_{ik}^*|g(U_i^T Z_k), \sigma_C^2\right)\right]^{I_{ik}^C}$$

# Framework

$$g(x) = (x-1)/(R_{\max}-1)$$

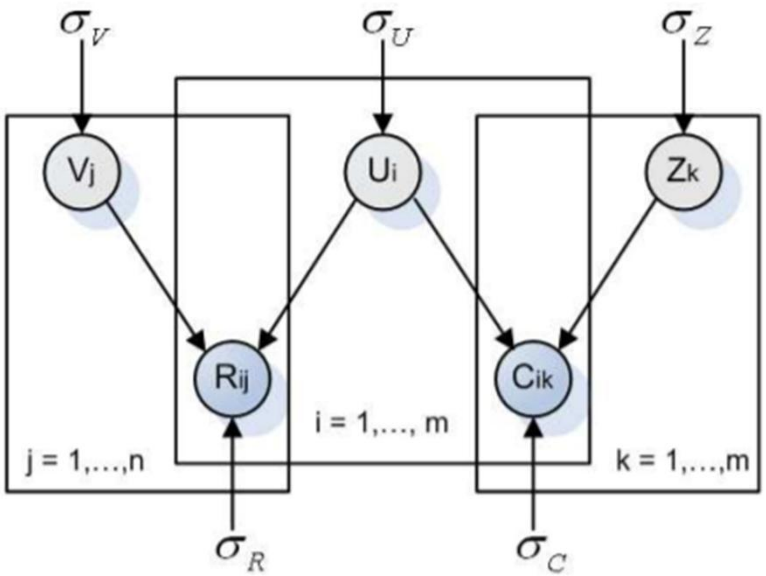
$$p(R|U,V,\sigma_R^2) = \prod_{i=1}^{m}\prod_{j=1}^{n}\mathcal{N}\left[\left(r_{ij}|g(U_i^T V_j),\sigma_R^2\right)\right]^{I_{ij}^R}$$

$$p(U|\sigma_U^2) = \prod_{i=1}^{m}\mathcal{N}(U_i|0,\sigma_U^2\mathbf{I})$$

$$p(V|\sigma_V^2) = \prod_{j=1}^{n}\mathcal{N}(V_j|0,\sigma_V^2\mathbf{I})$$

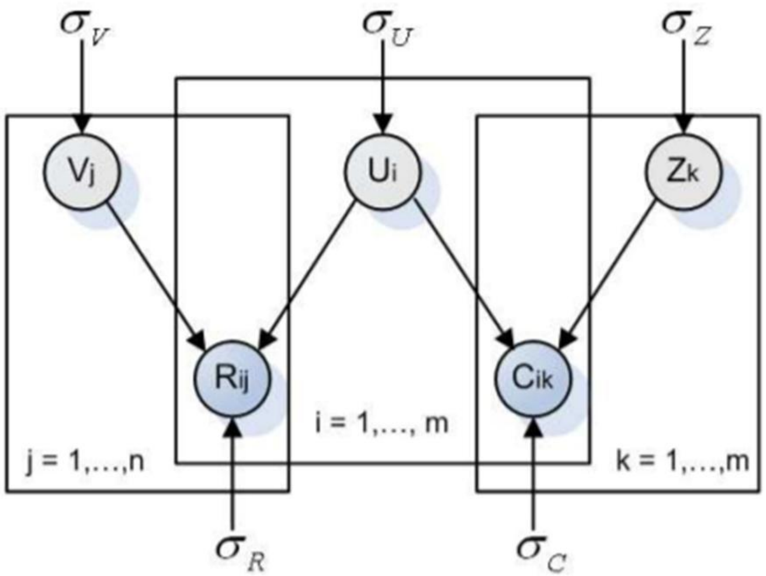
$$\begin{aligned} &p(U,V|R,\sigma_R^2,\sigma_U^2,\sigma_V^2) \\ &\quad\propto\ p(R|U,V,\sigma_R^2)p(U|\sigma_U^2)p(V|\sigma_V^2) \\ &\quad=\ \prod_{i=1}^{m}\prod_{j=1}^{n}\mathcal{N}\left[\left(r_{ij}|g(U_i^T V_j),\sigma_R^2\right)\right]^{I_{ij}^R} \\ &\quad\times\ \prod_{i=1}^{m}\mathcal{N}(U_i|0,\sigma_U^2\mathbf{I})\times\prod_{j=1}^{n}\mathcal{N}(V_j|0,\sigma_V^2\mathbf{I}) \end{aligned}$$

# Framework




$$\begin{aligned}
&\ln p(U, V, Z | C, R, \sigma_C^2, \sigma_R^2, \sigma_U^2, \sigma_V^2, \sigma_Z^2) = \\
&\quad -\frac{1}{2\sigma_R^2} \sum_{i=1}^{m} \sum_{j=1}^{n} I_{ij}^R (r_{ij} - g(U_i^T V_j))^2 \\
&\quad -\frac{1}{2\sigma_C^2} \sum_{i=1}^{m} \sum_{k=1}^{m} I_{ik}^C (c_{ik}^* - g(U_i^T Z_k))^2 \\
&\quad -\frac{1}{2\sigma_U^2} \sum_{i=1}^{m} U_i^T U_i - \frac{1}{2\sigma_V^2} \sum_{j=1}^{n} V_j^T V_j - \frac{1}{2\sigma_Z^2} \sum_{k=1}^{m} Z_k^T Z_k \\
&\quad -\frac{1}{2} \left( \left( \sum_{i=1}^{m} \sum_{j=1}^{n} I_{ij}^R \right) \ln\sigma_R^2 + \left( \sum_{i=1}^{m} \sum_{k=1}^{m} I_{ik}^C \right) \ln\sigma_C^2 \right) \\
&\quad -\frac{1}{2} \left( ml\ln\sigma_U^2 + nl\ln\sigma_V^2 + ml\ln\sigma_Z^2 \right) + \mathcal{C}, \qquad (8)
\end{aligned}$$

# Framework




$$\lambda_C = \sigma_R^2/\sigma_C^2,\ \lambda_U = \sigma_R^2/\sigma_U^2,\ \lambda_V = \sigma_R^2/\sigma_V^2$$

$$\lambda_Z = \sigma_R^2/\sigma_Z^2$$

$\Downarrow$

$$\lambda_U = \lambda_V = \lambda_Z$$

$$\mathcal{L}(R,C,U,V,Z) = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}^R (r_{ij} - g(U_i^T V_j))^2 + \frac{\lambda_C}{2}\sum_{i=1}^{m}\sum_{k=1}^{m} I_{ik}^C (c_{ik}^* - g(U_i^T Z_k))^2 + \frac{\lambda_U}{2}\|U\|_F^2 + \frac{\lambda_V}{2}\|V\|_F^2 + \frac{\lambda_Z}{2}\|Z\|_F^2, \quad (9)$$

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial U_i} &= \sum_{j=1}^{n} I_{ij}^R g'(U_i^T V_j)(g(U_i^T V_j) - r_{ij})V_j \\
&\quad + \lambda_C \sum_{j=1}^{m} I_{ik}^C g'(U_i^T Z_k)(g(U_i^T Z_k) - c_{ik}^*)Z_k + \lambda_U U_i, \\
\frac{\partial \mathcal{L}}{\partial V_j} &= \sum_{i=1}^{m} I_{ij}^R g'(U_i^T V_j)(g(U_i^T V_j) - r_{ij})U_i + \lambda_V V_j, \\
\frac{\partial \mathcal{L}}{\partial Z_k} &= \lambda_C \sum_{i=1}^{m} I_{ik}^C g'(U_i^T Z_k)(g(U_i^T Z_k) - c_{ik}^*)U_i + \lambda_Z Z_k, (10)
\end{aligned}$$

# Framework

$$\frac{\partial \mathcal{L}}{\partial U} = O(\rho_R l + \rho_C l)$$

$$\frac{\partial \mathcal{L}}{\partial V} = O(\rho_R l)$$

$$\frac{\partial \mathcal{L}}{\partial Z} = O(\rho_C l)$$

Computational time : linear with respect to the number of observations in the two sparse matrices.

Thus, the approach can scale on large datasets

# Experiment

1. How does our approach compare with the published state-of-the-art collaborative filtering algorithms?

2. How does the model parameter $\lambda\_C$ affect the accuracy of prediction?

3. What is the performance comparison on users with different observed ratings?

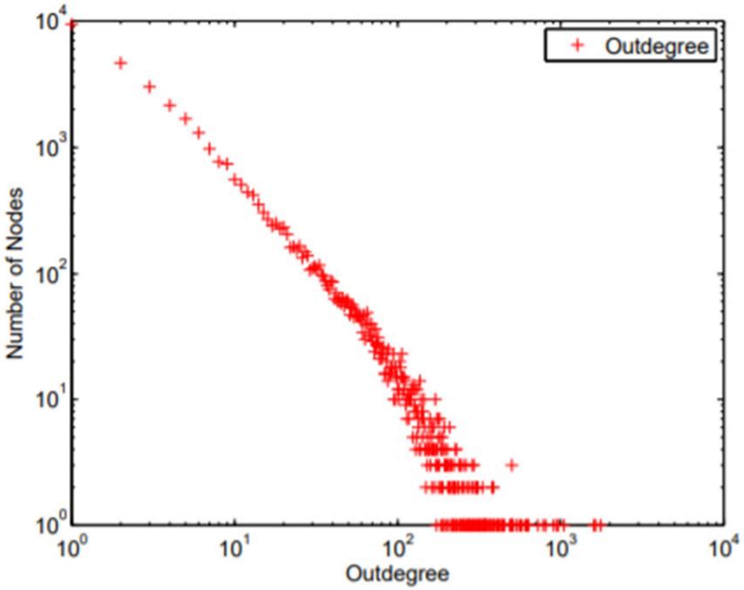
4. Can our algorithm achieve good performance even if users have no observed ratings?

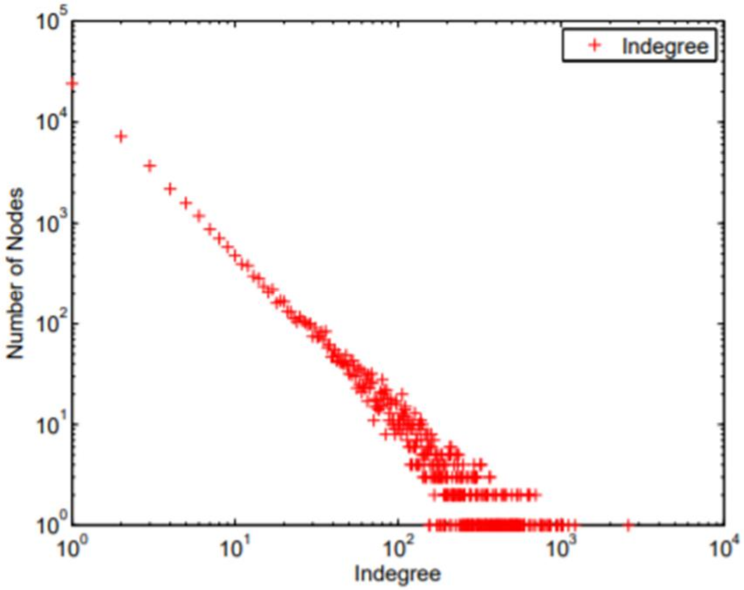
5. Is our algorithm efficient for large datasets?

# Experiment

**Table 1:** Statistics of User-Item Rating Matrix of Epinions

| Statistics | User | Item |
|---|---|---|
| Min. Num. of Rated | 1 | 1 |
| Max. Num. of Rated | 1022 | 2018 |
| Avg. Num. of Rated | 16.55 | 4.76 |



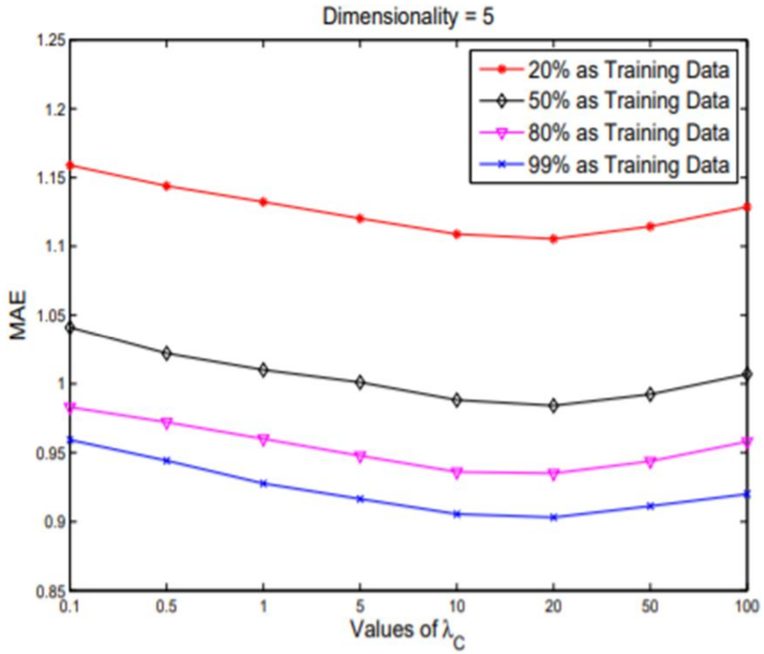



# Experiment

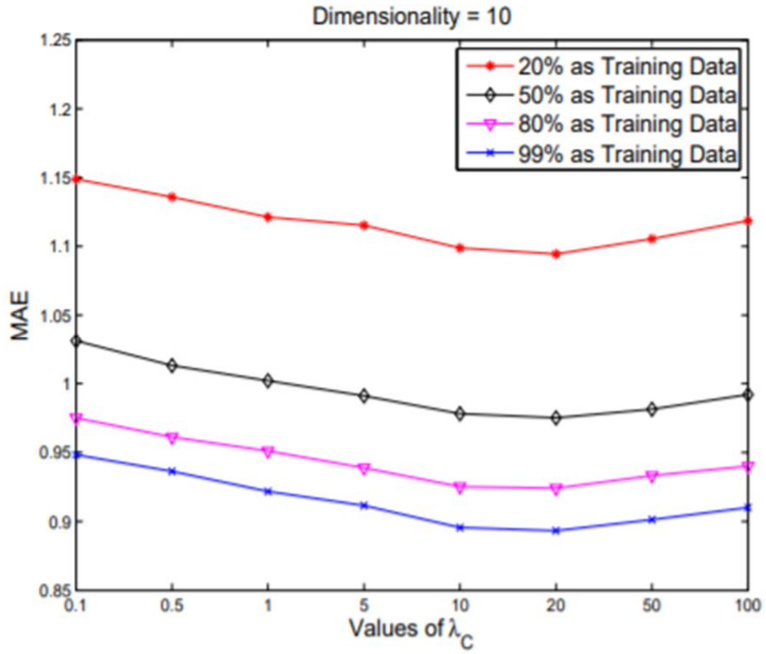
**Table 2: MAE comparison with other approaches (A smaller MAE value means a better performance)**

| Training Data | Dimensionality = 5 | | | | Dimensionality = 10 | | | |
|---|---|---|---|---|---|---|---|---|
| | MMMF | PMF | CPMF | SoRec | MMMF | PMF | CPMF | SoRec |
| 99% | 1.0008 | 0.9971 | 0.9842 | **0.9018** | 0.9916 | 0.9885 | 0.9746 | **0.8932** |
| 80% | 1.0371 | 1.0277 | 0.9998 | **0.9321** | 1.0275 | 1.0182 | 0.9923 | **0.9240** |
| 50% | 1.1147 | 1.0972 | 1.0747 | **0.9838** | 1.1012 | 1.0857 | 1.0632 | **0.9751** |
| 20% | 1.2532 | 1.2397 | 1.1981 | **1.1069** | 1.2413 | 1.2276 | 1.1864 | **1.0944** |

# Experiment

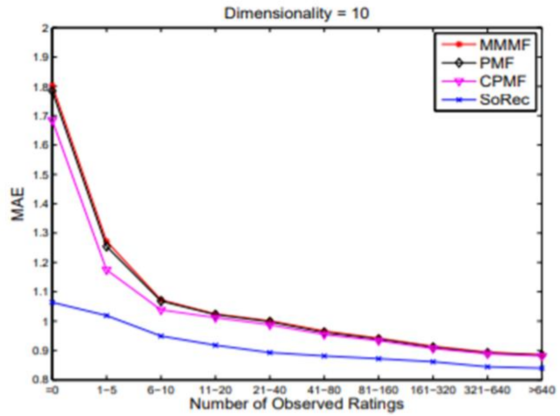



(a) Dimensionality=5

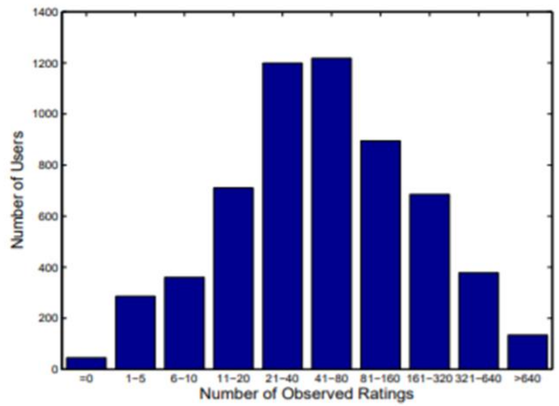



(b) Dimensionality=10

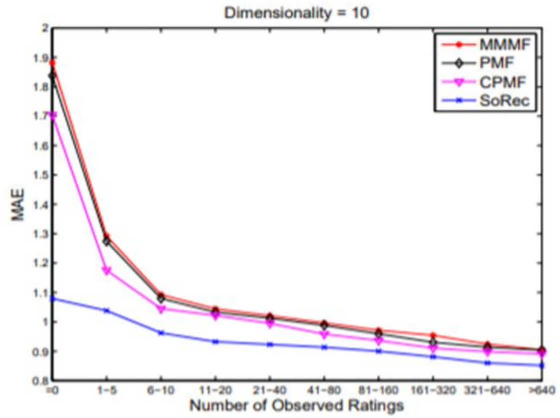
# Experiment



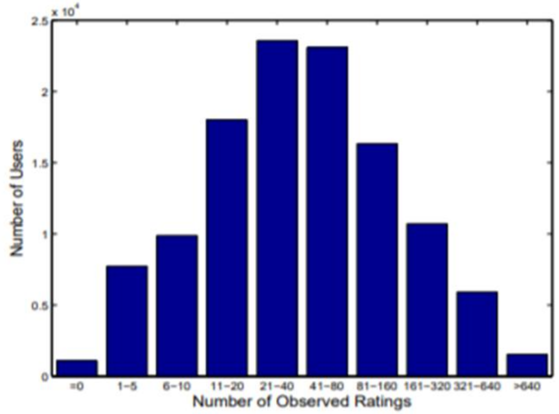

(a) Performance Comparison on Different User Rating Scales (99% as Training Data)




(b) Distribution of Testing Data (99% as Training Data)

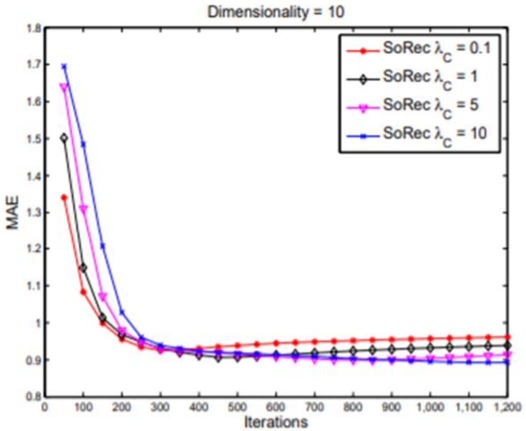



(c) Performance Comparison on Different User Rating Scales (80% as Training Data)

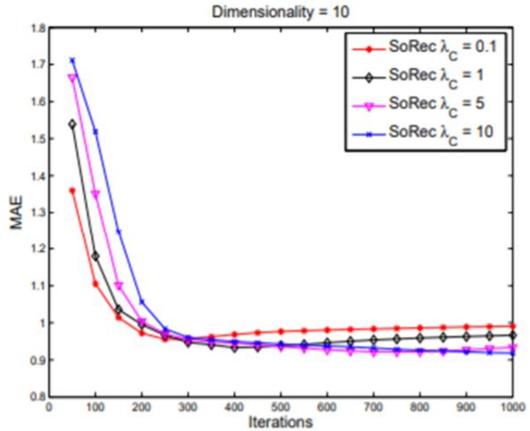



(d) Distribution of Testing Data (80% as Training Data)

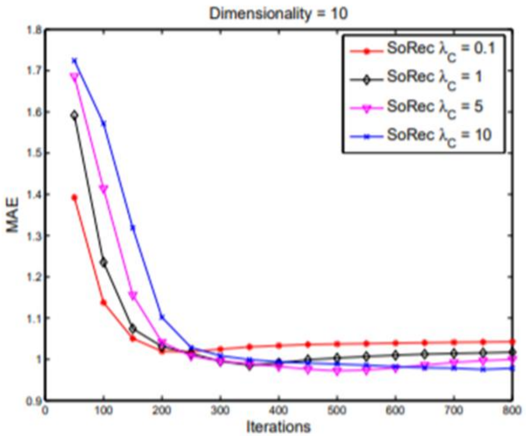
# Experiment



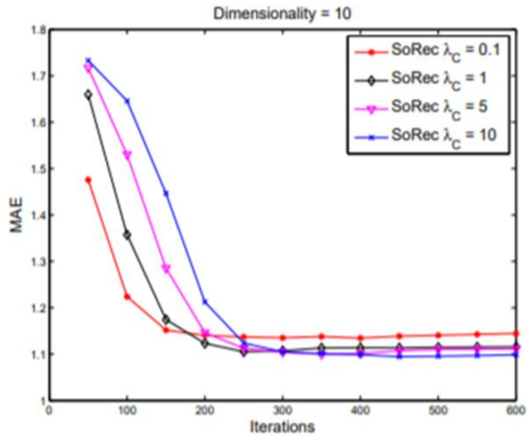

(a) 99% as Training Data




(b) 80% as Training Data




(c) 50% as Training Data




(d) 20% as Training Data

# Conclusion

**Conclusion**

* Experimental results: the approach outperforms the other state-of-the-art collaborative filtering algorithms

* Complexity analysis: it is scalable to very large datasets.

* Can also be used to predict connections on social network.

**Future work**

* Distrust information

* Diffusion process

# Introduction

## Problem

1. “trust relationships” are different from “social friendships”

2. assumption that users have similar tastes with other users they trust

3. online users spend more and more time on social network with real friends

# Framework


(a) Real World Social Recommendation (b) Social Network

| | $v_1$ | $v_2$ | $v_3$ | $v_4$ | $v_5$ |
|---|---|---|---|---|---|
| $u_1$ | 1 | | 2 | 3 | |
| $u_2$ | | 3 | | | 1 |
| $u_3$ | | 4 | | 5 | |
| $u_4$ | 5 | | | 4 | |
| $u_5$ | | 2 | 5 | | 4 |

(c) User-Item Rating Matrix

$$R \approx U^T V$$

U - low-dimensional user latent feature space
~~Z - factor matrix in the social network graph~~
V - low-dimensional item latent feature space

# Framework

$$\frac{1}{2}||R - U^T V||_F^2$$

$$\min_{U,V} \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{n} I_{ij}(R_{ij} - U_i^T V_j)^2$$

$$\min_{U,V} \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{n} I_{ij}(R_{ij} - U_i^T V_j)^2 + \frac{\lambda_1}{2}||U||_F^2 + \frac{\lambda_2}{2}||V||_F^2$$

# Framework – Social Regularization

$$\begin{aligned}\min_{U,V} \mathcal{L}_1(R,U,V) &= \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}(R_{ij} - U_i^T V_j)^2 \\ &+ \frac{\alpha}{2}\sum_{i=1}^{m} \|U_i - \frac{1}{|\mathcal{F}^+(i)|}\sum_{f\in\mathcal{F}^+(i)} U_f\|_F^2 \\ &+ \frac{\lambda_1}{2}\|U\|_F^2 + \frac{\lambda_2}{2}\|V\|_F^2, \qquad (5)\end{aligned}$$

$$\begin{aligned}\min_{U,V} \mathcal{L}_1(R,U,V) = &\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}(R_{ij} - U_i^T V_j)^2 \\ &+ \frac{\alpha}{2}\sum_{i=1}^{m} \|U_i - \frac{\sum_{f\in\mathcal{F}^+(i)} Sim(i,f)\times U_f}{\sum_{f\in\mathcal{F}^+(i)} Sim(i,f)}\|_F^2, \\ &+ \frac{\lambda_1}{2}\|U\|_F^2 + \frac{\lambda_2}{2}\|V\|_F^2. \qquad (8)\end{aligned}$$

$$\begin{aligned}\frac{\partial \mathcal{L}_1}{\partial U_i} = &\sum_{j=1}^{n} I_{ij}(U_i^T V_j - R_{ij})V_j + \lambda_1 U_i \\ &+ \alpha(U_i - \frac{\sum_{f\in\mathcal{F}^+(i)} Sim(i,f)\times U_f}{\sum_{f\in\mathcal{F}^+(i)} Sim(i,f)}) \\ &+ \alpha \sum_{g\in\mathcal{F}^-(i)} \frac{-Sim(i,g)(U_g - \frac{\sum_{f\in\mathcal{F}^+(g)} Sim(g,f)\times U_f}{\sum_{f\in\mathcal{F}^+(g)} Sim(g,f)})}{\sum_{f\in\mathcal{F}^+(g)} Sim(g,f)}, \\ \frac{\partial \mathcal{L}_1}{\partial V_j} = &\sum_{i=1}^{m} I_{ij}(U_i^T V_j - R_{ij})U_i + \lambda_2 V_j. \qquad (9)\end{aligned}$$

# Framework – Social Regularization

$$\frac{\beta}{2}\sum_{i=1}^{m}\sum_{f\in\mathcal{F}^{+}(i)} Sim(i,f)\|U_i - U_f\|_F^2,$$

$$\begin{aligned}\min_{U,V}\mathcal{L}_2(R,U,V) &= \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}(R_{ij}-U_i^T V_j)^2 \\ &+ \frac{\beta}{2}\sum_{i=1}^{m}\sum_{f\in\mathcal{F}^{+}(i)} Sim(i,f)\|U_i - U_f\|_F^2 \\ &+ \lambda_1\|U\|_F^2 + \lambda_2\|V\|_F^2. \qquad (11)\end{aligned}$$

# Framework – Social Regularization

$$Sim(i,f) = \frac{\sum\limits_{j \in I(i) \cap I(f)} R_{ij} \cdot R_{fj}}{\sqrt{\sum\limits_{j \in I(i) \cap I(f)} R_{ij}^2} \cdot \sqrt{\sum\limits_{j \in I(i) \cap I(f)} R_{fj}^2}},$$

: VSS

$$Sim(i,f) = \frac{\sum\limits_{j \in I(i) \cap I(f)} (R_{ij} - \overline{R}_i) \cdot (R_{fj} - \overline{R}_f)}{\sqrt{\sum\limits_{j \in I(i) \cap I(f)} (R_{ij} - \overline{R}_i)^2} \cdot \sqrt{\sum\limits_{j \in I(i) \cap I(f)} (R_{fj} - \overline{R}_f)^2}},$$

: PCC

$f(x) = (x+1)/2$

# Experiment

**Table 1: Statistics of User-Item Matrix of Douban**

| Statistics | User | Item |
|---|---|---|
| Min. Num. of Ratings | 1 | 1 |
| Max. Num. of Ratings | 6,328 | 49,504 |
| Avg. Num. of Ratings | 129.98 | 287.51 |

**Table 2: Statistics of Friend Network of Douban**

| Statistics | Friends per User |
|---|---|
| Max. Num. | 986 |
| Avg. Num. | 13.07 |

**Table 3: Statistics of User-Item Matrix of Epinions**

| Statistics | User | Item |
|---|---|---|
| Max. Num. of Ratings | 1960 | 7082 |
| Avg. Num. of Ratings | 12.21 | 7.56 |

**Table 4: Statistics of Trust Network of Epinions**

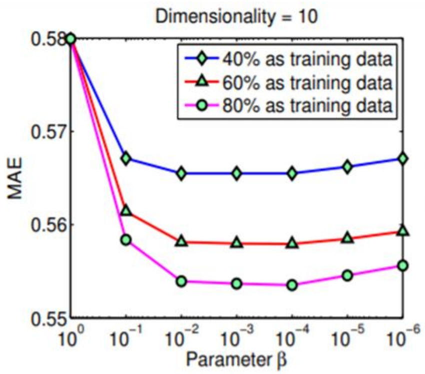
| Statistics | Trust per User | Be Trusted per User |
|---|---|---|
| Max. Num. | 1763 | 2443 |
| Avg. Num. | 9.91 | 9.91 |

# Experiment

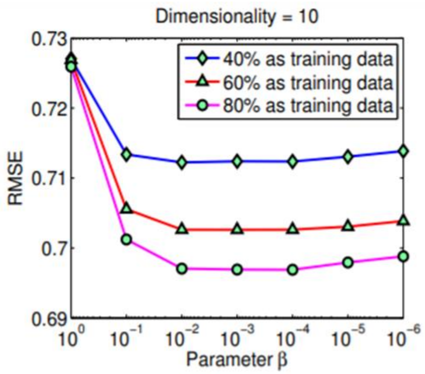
Table 5: Performance Comparisons (Dimensionality = 10)

| Dataset | Training | Metrics | UserMean | ItemMean | NMF | PMF | RSTE | $SR1_{vss}$ | $SR1_{pcc}$ | $SR2_{vss}$ | $SR2_{pcc}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Douban | 80% | MAE | 0.6809 | 0.6288 | 0.5732 | 0.5693 | 0.5643 | 0.5579 | 0.5576 | 0.5548 | **0.5543** |
| | | Improve | 18.59% | 11.85% | 3.30% | 2.63% | 1.77% | | | | |
| | | RMSE | 0.8480 | 0.7898 | 0.7225 | 0.7200 | 0.7144 | 0.7026 | 0.7022 | 0.6992 | **0.6988** |
| | | Improve | 17.59% | 11.52% | 3.28% | 2.94% | 2.18% | | | | |
| | 60% | MAE | 0.6823 | 0.6300 | 0.5768 | 0.5737 | 0.5698 | 0.5627 | 0.5623 | 0.5597 | **0.5593** |
| | | Improve | 18.02% | 11.22% | 3.03% | 2.51% | 1.84% | | | | |
| | | RMSE | 0.8505 | 0.7926 | 0.7351 | 0.7290 | 0.7207 | 0.7081 | 0.7078 | 0.7046 | **0.7042** |
| | | Improve | 17.20% | 11.15% | 4.20% | 3.40% | 2.29% | | | | |
| | 40% | MAE | 0.6854 | 0.6317 | 0.5899 | 0.5868 | 0.5767 | 0.5706 | 0.5702 | 0.5690 | **0.5685** |
| | | Improve | 17.06% | 10.00% | 3.63% | 3.12% | 1.42% | | | | |
| | | RMSE | 0.8567 | 0.7971 | 0.7482 | 0.7411 | 0.7295 | 0.7172 | 0.7169 | 0.7129 | **0.7125** |
| | | Improve | 16.83% | 10.61% | 4.77% | 3.86% | 2.33% | | | | |
| Epinions | 90% | MAE | 0.9134 | 0.9768 | 0.8712 | 0.8651 | 0.8367 | 0.8290 | 0.8287 | 0.8258 | **0.8256** |
| | | Improve | 9.61% | 15.48% | 5.23% | 4.57% | 1.33% | | | | |
| | | RMSE | 1.1688 | 1.2375 | 1.1621 | 1.1544 | 1.1094 | 1.0792 | 1.0790 | 1.0744 | **1.0739** |
| | | Improve | 8.12% | 13.22% | 7.59% | 6.97% | 3.20% | | | | |
| | 80% | MAE | 0.9285 | 0.9913 | 0.8951 | 0.8886 | 0.8537 | 0.8493 | 0.8491 | 0.8447 | **0.8443** |
| | | Improve | 9.07% | 14.83% | 5.68% | 4.99% | 1.10% | | | | |
| | | RMSE | 1.1817 | 1.2584 | 1.1832 | 1.1760 | 1.1256 | 1.1016 | 1.1013 | 1.0958 | **1.0954** |
| | | Improve | 7.30% | 12.95% | 7.42% | 6.85% | 2.68% | | | | |

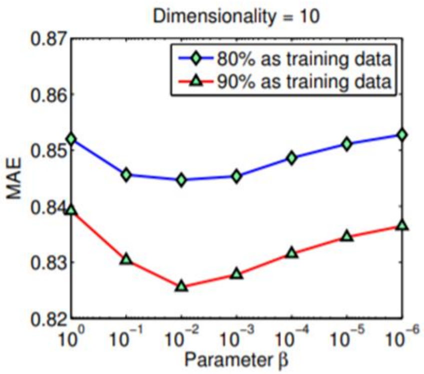
# Experiment



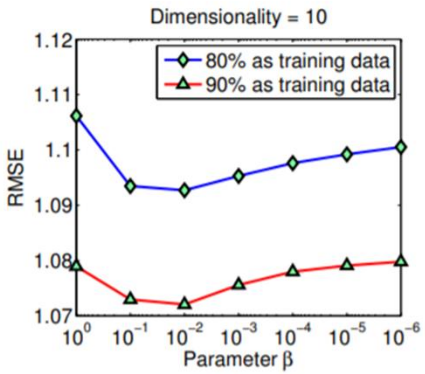

(a) Douban (MAE)




(b) Douban (RMSE)




(c) Epinions (MAE)




(d) Epinions (RMSE)

**Table 6: Similarity Analysis (Dimensionality = 10)**

| Dataset | Training | Metrics | SR2 Sim=1 | SR2 Sim=Ran | $SR2_{vss}$ | $SR2_{pcc}$ |
|---|---|---|---|---|---|---|
| Douban | 80% | MAE | 0.5579 | 0.5592 | 0.5548 | 0.5543 |
| | | RMSE | 0.7034 | 0.7047 | 0.6992 | 0.6988 |
| | 60% | MAE | 0.5631 | 0.5643 | 0.5597 | 0.5593 |
| | | RMSE | 0.7083 | 0.7098 | 0.7046 | 0.7042 |
| | 40% | MAE | 0.5724 | 0.5737 | 0.5690 | 0.5685 |
| | | RMSE | 0.7195 | 0.7209 | 0.7129 | 0.7125 |
| Epinions | 90% | MAE | 0.8324 | 0.8345 | 0.8258 | 0.8256 |
| | | RMSE | 1.0794 | 1.0809 | 1.0744 | 1.0739 |
| | 80% | MAE | 0.8511 | 0.8530 | 0.8447 | 0.8443 |
| | | RMSE | 1.1002 | 1.1018 | 1.0958 | 1.0954 |

# Conclusion

**Conclusion**

* Two general algorithms are proposed that imposed social regularization using PCC and VSS

* Quite generic method also can be applied to trust aware recommendation problems

* Comparison

**Future work**

* Categorical cluster

* Clicking behavior and Tagging record

감사합니다.