# CMSC5733 Social Computing

Irwin King

The Chinese University of Hong Kong

king@cse.cuhk.edu.hk

# Social Recommender Systems

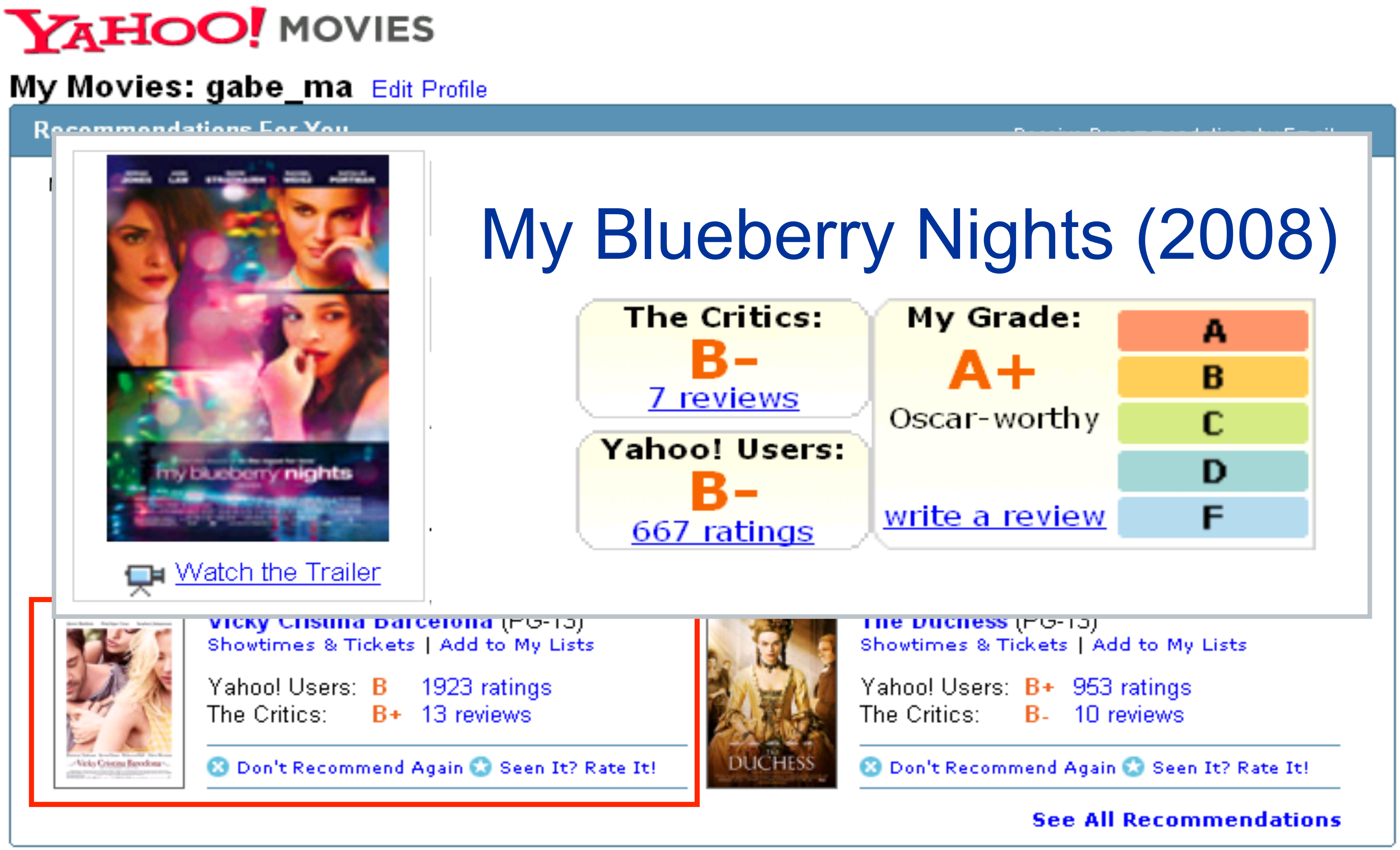
- Introduction
- Collaborative Filtering
- Trust-aware Recommender Systems
- Social-based Recommender Systems
- Web Site Recommendation

# Social Recommendation Using Probabilistic Matrix Factorization

[Hao Ma, et al., CIKM2008]

# Challenges

- Data sparsity problem



**My Movies: gabe_ma** Edit Profile

Recommendations For You

My Blueberry Nights (2008)

**The Critics:** B- 7 reviews

**Yahoo! Users:** B- 667 ratings

**My Grade:** A+ Oscar-worthy

write a review

Vicky Cristina Barcelona (PG-13)

Showtimes & Tickets | Add to My Lists

| | | |
|---|---|---|
| Yahoo! Users: | B | 1923 ratings |
| The Critics: | B+ | 13 reviews |

Don't Recommend Again Seen It? Rate It!

The Duchess (PG-13)

Showtimes & Tickets | Add to My Lists

| | | |
|---|---|---|
| Yahoo! Users: | B+ | 953 ratings |
| The Critics: | B- | 10 reviews |

Don't Recommend Again Seen It? Rate It!

**See All Recommendations**

# Challenges

My Movie Ratings

**The Pursuit of Happyness** (PG-13, 1 hr. 57 min.)
Buy DVD | Add to My Lists

Yahoo! Users: B+ 38992 ratings
The Critics: B- 13 reviews

My Rating: A+

**Finding Nemo** (G, 1 hr. 40 min.)
Buy DVD | Add to My Lists

Yahoo! Users: B+ 137394 ratings
The Critics: A- 14 reviews

My Rating: A

**My Blueberry Nights** (PG-13, 1 hr. 30 min.)
Buy DVD | Add to My Lists

Yahoo! Users: B- 756 ratings
The Critics: B- 7 reviews

My Rating: A+

**Cold Mountain** (R, 2 hrs. 35 min.)
Buy DVD | Add to My Lists

Yahoo! Users: B 38986 ratings
The Critics: B+ 10 reviews

My Rating: B+

**The Lord of the Rings: The Fellowship of the Ring**
Buy DVD | Add to My Lists

Yahoo! Users: A- 110957 ratings
The Critics: A 15 reviews

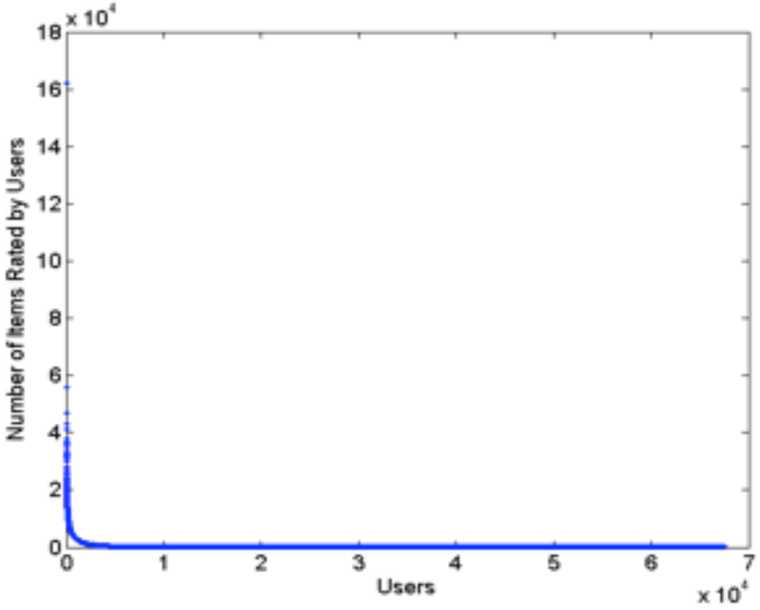
My Rating: A

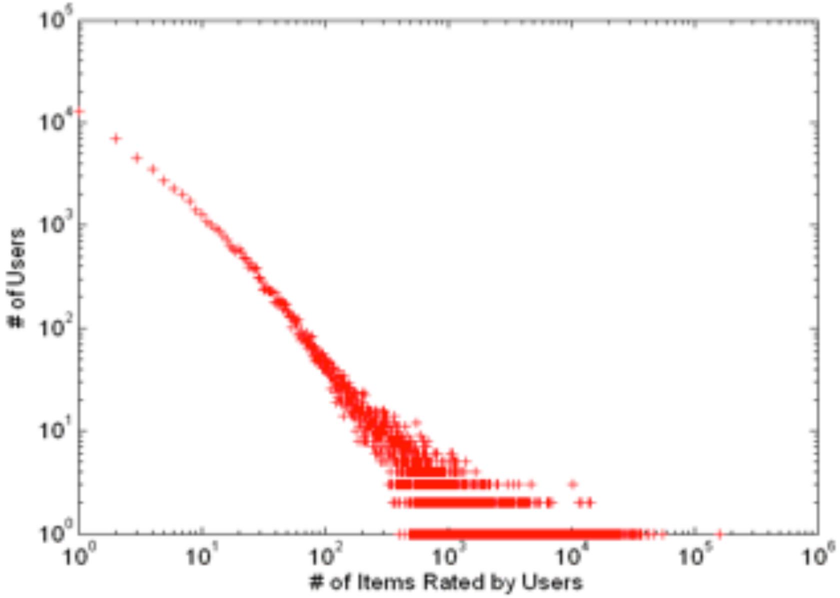
**Shrek 2** (PG, 1 hr. 32 min.)
Buy DVD | Add to My Lists

Yahoo! Users: B+ 150368 ratings
The Critics: B 15 reviews

My Rating: B

# Number of Ratings per User





Extracted From Epinions.com

114,222 users, 754,987 items and 13,385,713 ratings

# Challenges

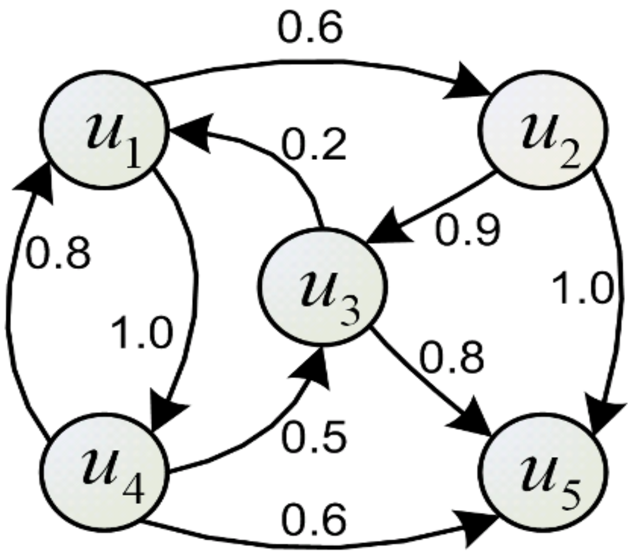
- Traditional recommender systems ignore the social connections between users

Recommendations from friends

# Motivations

- "Yes, there is a correlation - from social networks to personal behavior on the web"
- Parag Singla and Matthew Richardson (WWW'08)
  - Analyze the who talks to whom social network over 10 million people with their related search results
  - People who chat with each other are more likely to share the same or similar interests
- To improve the recommendation accuracy and solve the data sparsity problem, users' social network should be taken into consideration

# Problem Definition



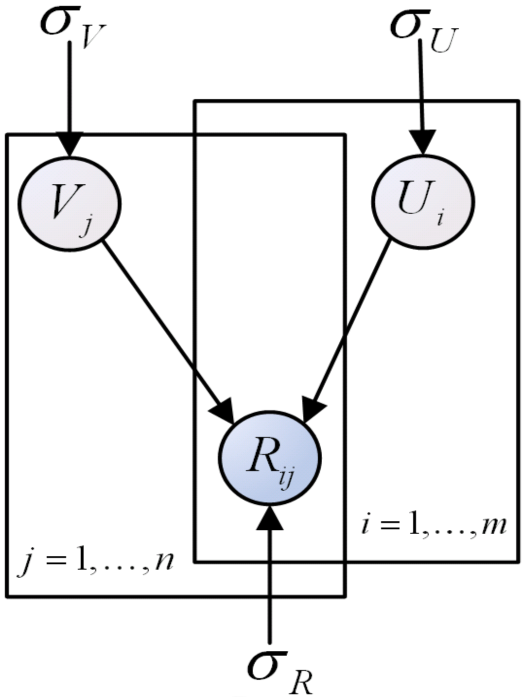
Social Trust Graph

|  | $v_1$ | $v_2$ | $v_3$ | $v_4$ | $v_5$ | $v_6$ |
|---|---|---|---|---|---|---|
| $u_1$ |  | 5 | 2 |  | 3 |  |
| $u_2$ | 4 |  |  | 3 |  | 4 |
| $u_3$ |  |  | 2 |  |  | 2 |
| $u_4$ | 5 |  |  | 3 |  |  |
| $u_5$ |  | 5 | 5 |  |  | 3 |

User-Item Rating Matrix

# User-Item Matrix Factorization

|  | $v_1$ | $v_2$ | $v_3$ | $v_4$ | $v_5$ | $v_6$ |
|---|---|---|---|---|---|---|
| $u_1$ |  | 5 | 2 |  | 3 |  |
| $u_2$ | 4 |  |  | 3 |  | 4 |
| $u_3$ |  |  | 2 |  |  | 2 |
| $u_4$ | 5 |  |  | 3 |  |  |
| $u_5$ |  | 5 | 5 |  |  | 3 |



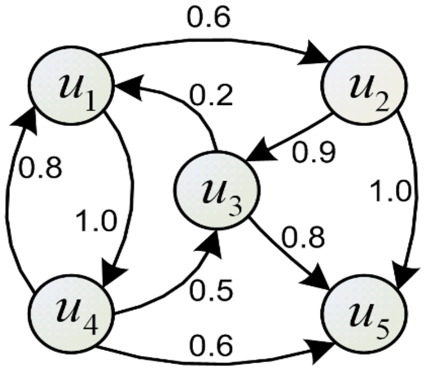
$$p(R|U, V, \sigma_R^2) = \prod_{i=1}^{m} \prod_{j=1}^{n} \left[ \mathcal{N}\left( R_{ij} | g(U_i^T V_j), \sigma_R^2 \right) \right]^{I_{ij}^R}$$

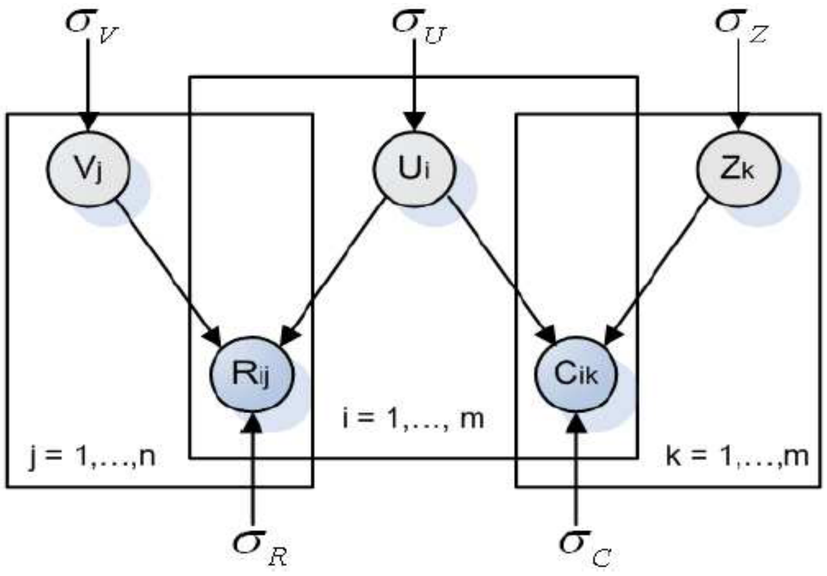
$$p(U|\sigma_U^2) = \prod_{i=1}^{m} \mathcal{N}(U_i|0, \sigma_U^2 \mathbf{I}) \qquad p(V|\sigma_V^2) = \prod_{j=1}^{n} \mathcal{N}(V_j|0, \sigma_V^2 \mathbf{I})$$

R. Salakhutdinov and A. Mnih (NIPS'08)

# SoRec

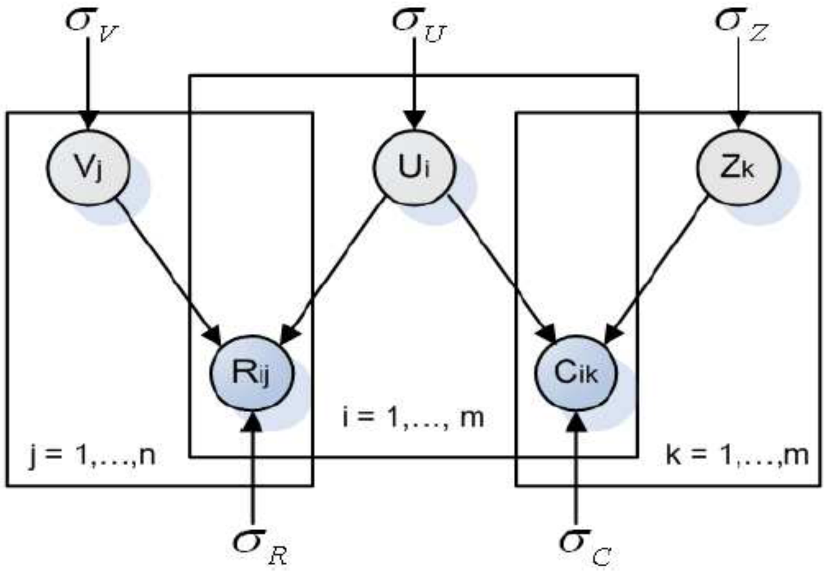
| | $v_1$ | $v_2$ | $v_3$ | $v_4$ | $v_5$ | $v_6$ |
|---|---|---|---|---|---|---|
| $u_1$ | | 5 | 2 | | 3 | |
| $u_2$ | 4 | | | 3 | | 4 |
| $u_3$ | | | 2 | | | 2 |
| $u_4$ | 5 | | | 3 | | |
| $u_5$ | | 5 | 5 | | | 3 |





SoRec

# SoRec



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

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

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

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

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

# SoRec

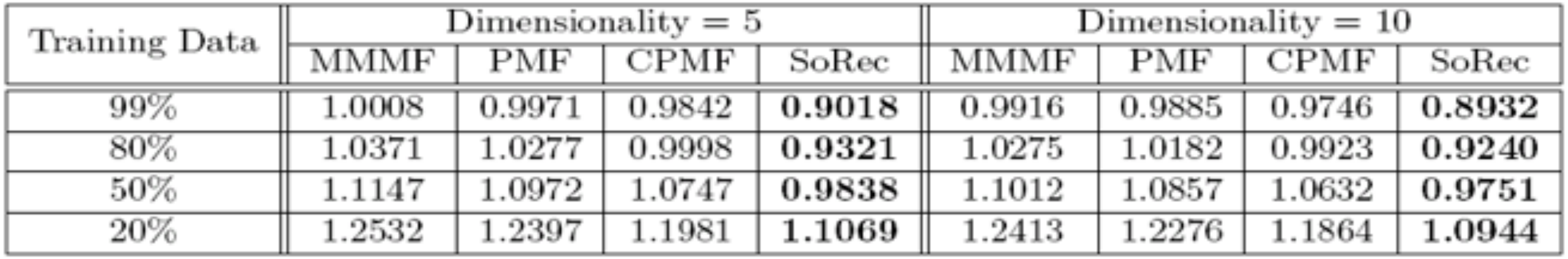
$$
\begin{aligned}
\frac{\partial \mathcal{L}}{\partial U_i} &= \sum_{j=1}^{n} I_{ij}^{R} g'(U_i^T V_j)(g(U_i^T V_j) - r_{ij})V_j \\
&+ \lambda_C \sum_{j=1}^{m} I_{ik}^{C} g'(U_i^T Z_k)(g(U_i^T Z_k) - c_{ik}^{*})Z_k + \lambda_U U_i, \\
\frac{\partial \mathcal{L}}{\partial V_j} &= \sum_{i=1}^{m} I_{ij}^{R}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

# Complexity Analysis

- For the Objective Function $O(\rho_R l + \rho_C l)$
- For $\frac{\partial \mathcal{L}}{\partial U}$ the complexity is $O(\rho_R l + \rho_C l)$
- For $\frac{\partial \mathcal{L}}{\partial V}$ the complexity is $O(\rho_R l)$
- For $\frac{\partial \mathcal{L}}{\partial Z}$ the complexity is $O(\rho_C l)$
- In general, the complexity of our method is linear with the observations in these two matrices

# Experimental Analysis

- Table: 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** |

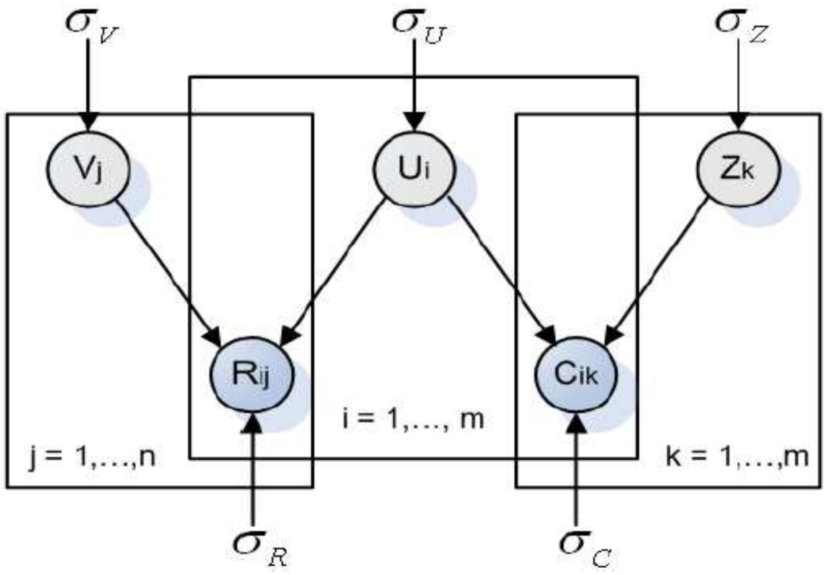
MMMF:
J.D.M Rennie and N. Srebro
(ICML'05)

PMF & CPMF:
R. Salakhutdinov and A. Mnih
(NIPS'08)

Epinions: 40,163 users who rated 139,529 items with totally 664,824 ratings

# Disadvantages of SoRec

- Lack of interpretability
- Does not reflect the real-world process

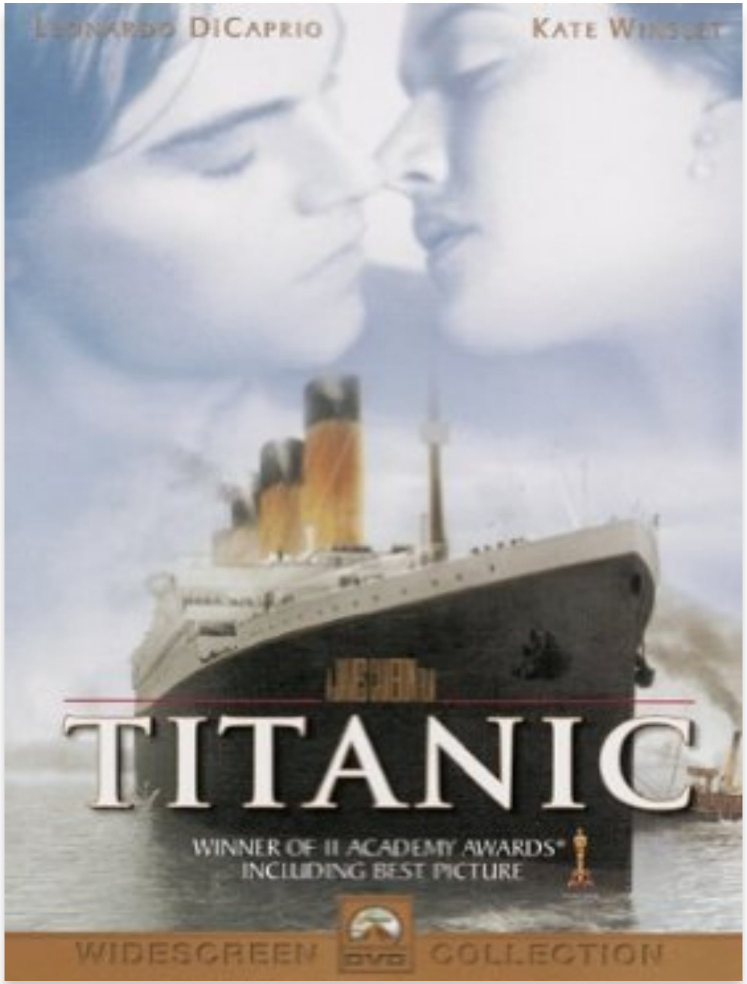


SoRec

# Learning to Recommend with Social Trust Ensemble

[Hao Ma, et al., SIGIR2009]

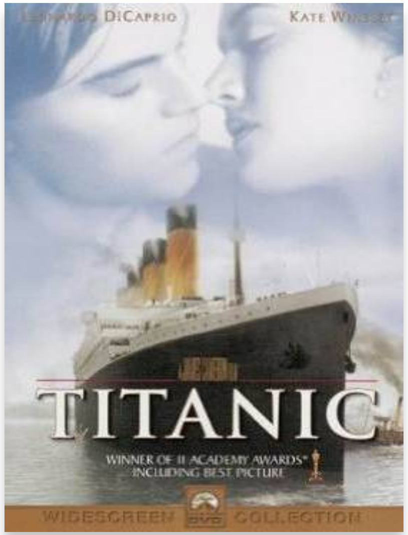
# 1st Motivation



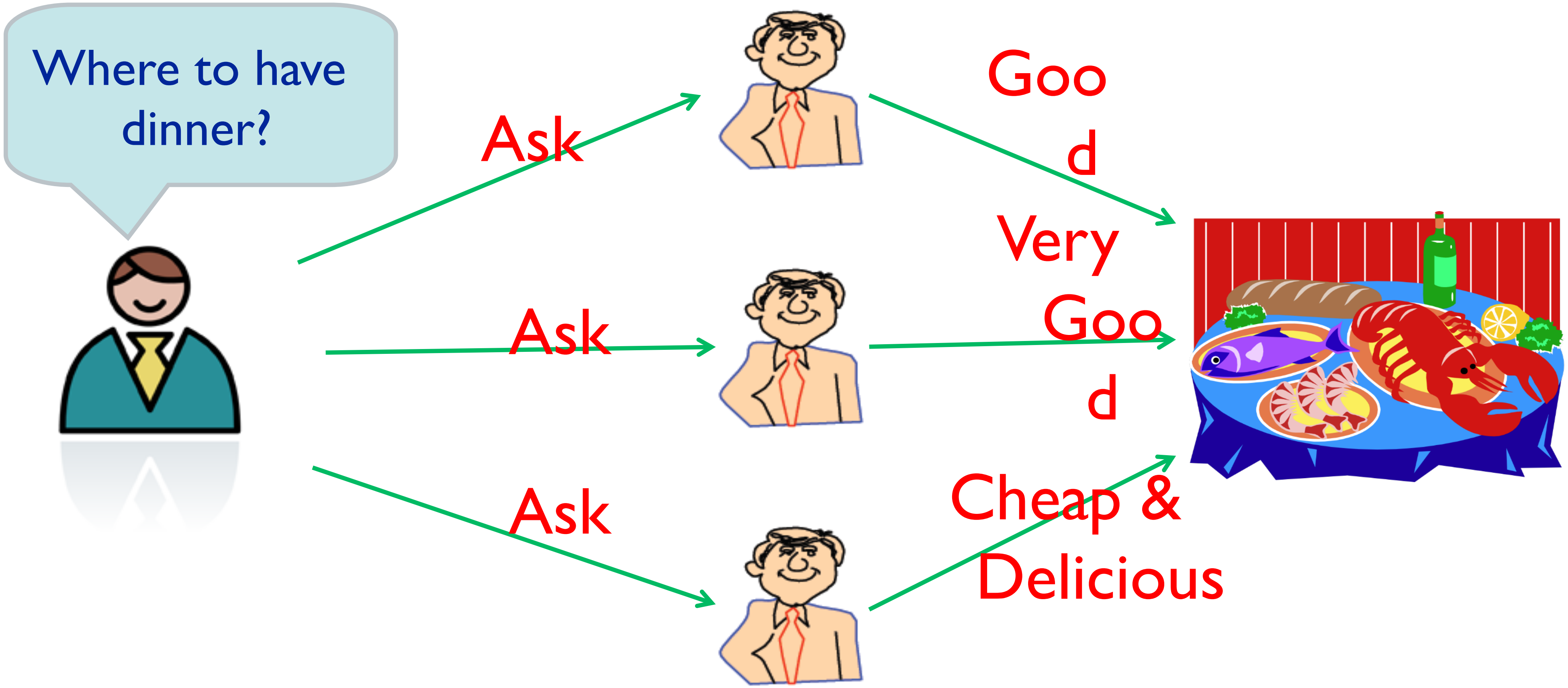
# 1st Motivation

# 1st Motivation

- Users have their own characteristics, and they have different tastes on different items, such as movies, books, music, articles, food, etc.



# 2nd Motivation



Where to have dinner?

Ask

Ask

Ask

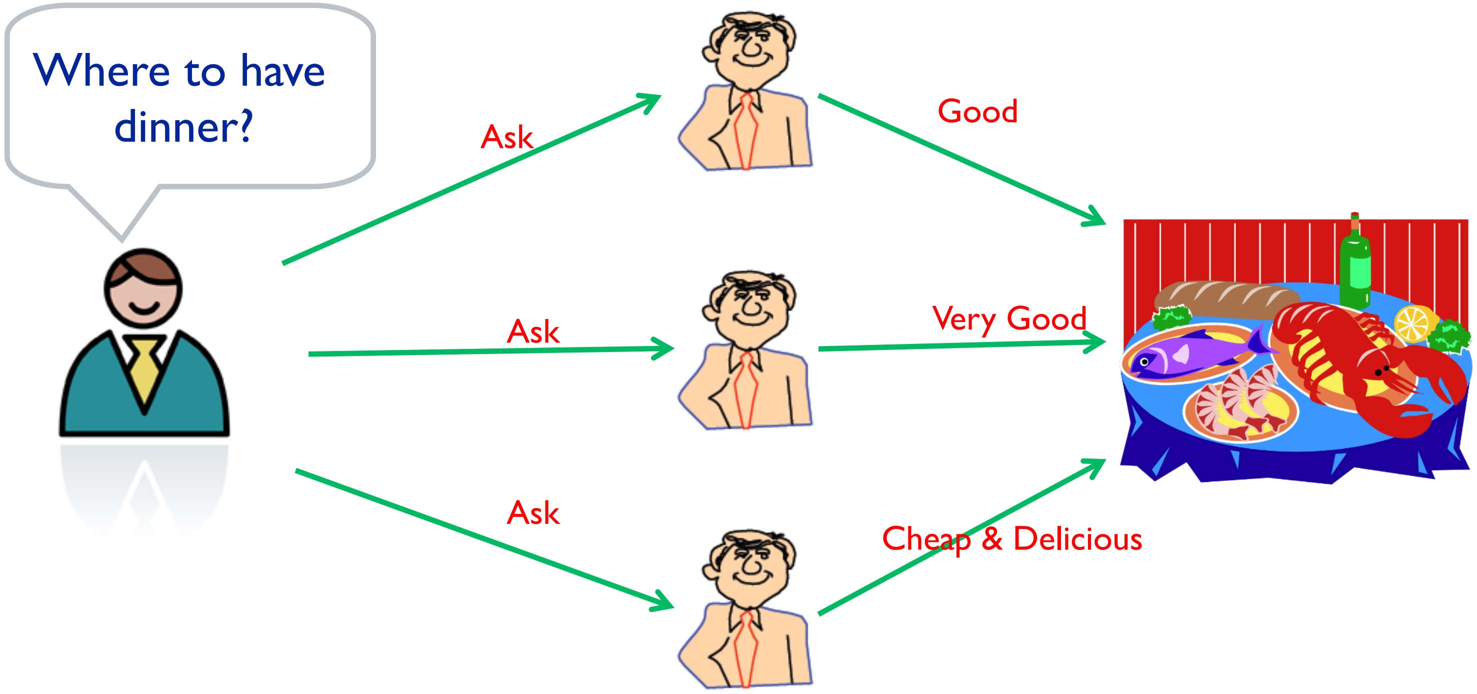
Good

Very Good

Cheap & Delicious

# 2nd Motivation

- Users can be easily influenced by the friends they trust, and prefer their friends' recommendations.

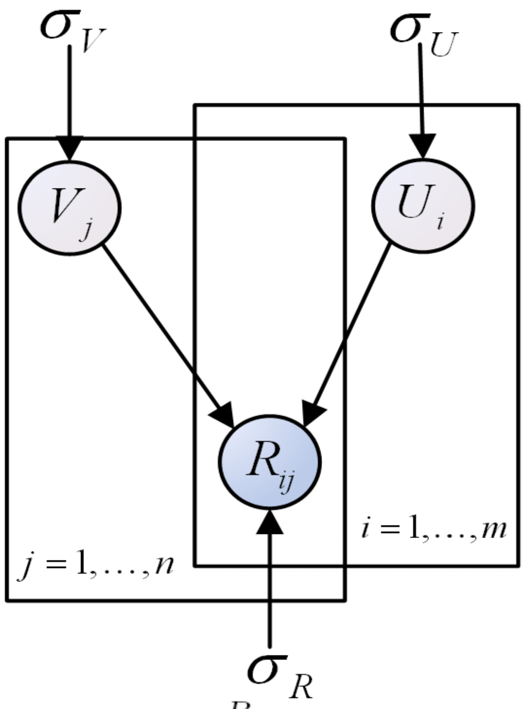


# Motivations

- Users have their own characteristics, and they have different tastes on different items, such as movies, books, music, articles, food, etc.
- Users can be easily influenced by the friends they trust, and prefer their friends' recommendations.
- One user's final decision is the balance between his/her own taste and his/her trusted friends' favors.

# User-Item Matrix Factorization

|  | $v_1$ | $v_2$ | $v_3$ | $v_4$ | $v_5$ | $v_6$ |
|---|---|---|---|---|---|---|
| $u_1$ |  | 5 | 2 |  | 3 |  |
| $u_2$ | 4 |  |  | 3 |  | 4 |
| $u_3$ |  |  | 2 |  |  | 2 |
| $u_4$ | 5 |  |  | 3 |  |  |
| $u_5$ |  | 5 | 5 |  |  | 3 |



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

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

[R. Salakhutdinov, et al., NIPS2008]

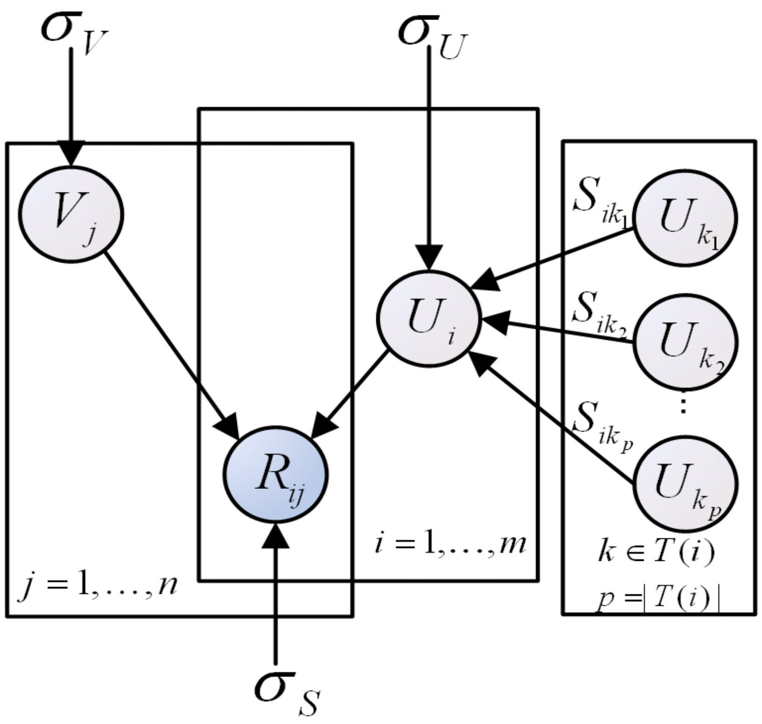
# Recommendations by Trusted Friends

$$\widehat{R}_{ik} = \frac{\sum_{j \in \mathcal{T}(i)} R_{jk} S_{ij}}{|\mathcal{T}(i)|}$$

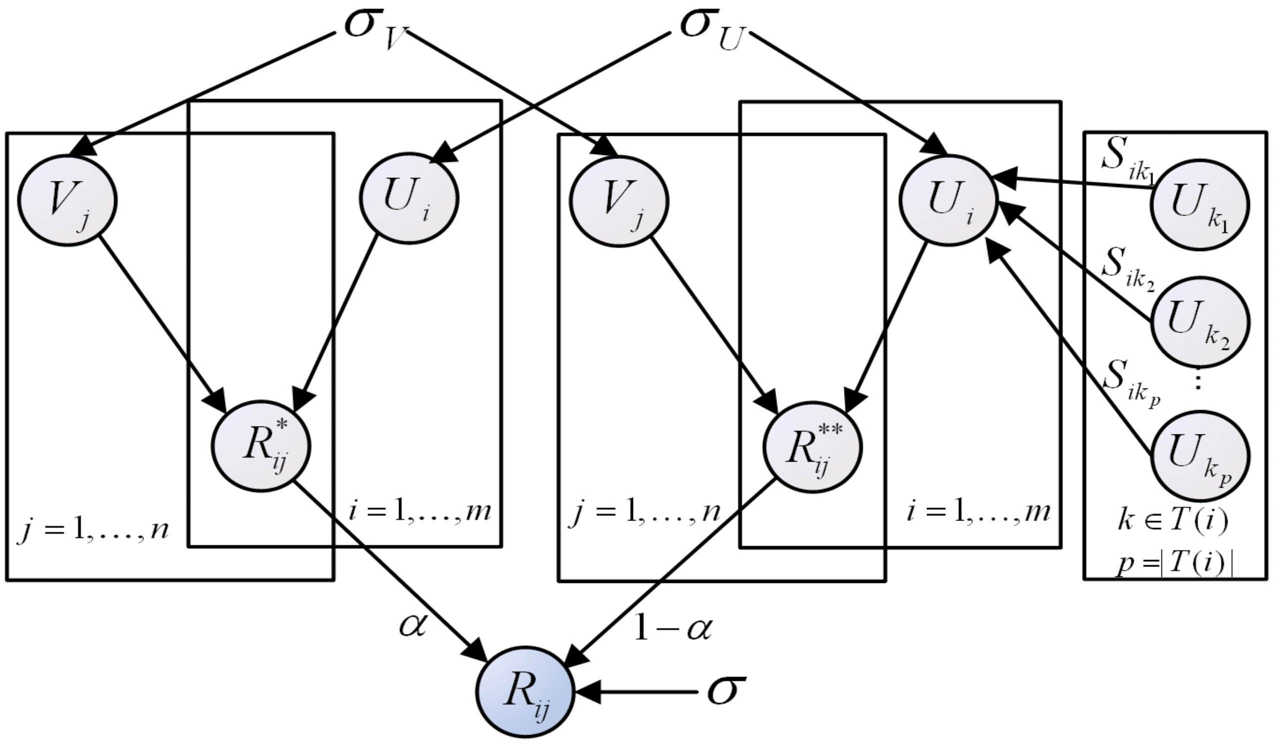
$$\widehat{R}_{ik} = \sum_{j \in \mathcal{T}(i)} R_{jk} S_{ij}$$

$$p(R|S, U, V, \sigma_R^2) =$$

$$\prod_{i=1}^{m} \prod_{j=1}^{n} \left[ \mathcal{N}\left( R_{ij} | g(\sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T V_j), \sigma_S^2 \right) \right]^{I_{ij}^R}$$



# Recommendation with Social Trust Ensemble



$$\prod_{i=1}^{m}\prod_{j=1}^{n}\left[\mathcal{N}\left(R_{ij}|g(\alpha U_i^T V_j + (1-\alpha)\sum_{k\in\mathcal{T}(i)} S_{ik}U_k^T V_j), \sigma^2\right)\right]^{I_{ij}^R}$$

# Recommendation with Social Trust Ensemble

$$
\begin{aligned}
&\mathcal{L}(R,S,U,V)\\
&=\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}^{R}(R_{ij}-g(\alpha U_i^T V_j+(1-\alpha)\sum_{k\in\mathcal{T}(i)} S_{ik}U_k^T V_j))^2\\
&+\frac{\lambda_U}{2}\|U\|_F^2+\frac{\lambda_V}{2}\|V\|_F^2, \qquad (15)
\end{aligned}
$$

$$
\begin{aligned}
\frac{\partial\mathcal{L}}{\partial U_i} =& \alpha\sum_{j=1}^{n} I_{ij}^{R} g'(\alpha U_i^T V_j+(1-\alpha)\sum_{k\in\mathcal{T}(i)} S_{ik}U_k^T V_j)V_j\\
&\times(g(\alpha U_i^T V_j+(1-\alpha)\sum_{k\in\mathcal{T}(i)} S_{ik}U_k^T V_j)-R_{ij})\\
&+(1-\alpha)\sum_{p\in\mathcal{B}(i)}\sum_{j=1}^{n} I_{pj}^{R} g'(\alpha U_p^T V_j+(1-\alpha)\sum_{k\in\mathcal{T}(p)} S_{pk}U_k^T V_j)\\
&\times(g(\alpha U_p^T V_j+(1-\alpha)\sum_{k\in\mathcal{T}(p)} S_{pk}U_k^T V_j)-R_{pj})S_{pi}V_j\\
&+\lambda_U U_i,
\end{aligned}
$$

$$
\begin{aligned}
\frac{\partial\mathcal{L}}{\partial V_j} =& \sum_{i=1}^{m} I_{ij}^{R} g'(\alpha U_i^T V_j+(1-\alpha)\sum_{k\in\mathcal{T}(i)} S_{ik}U_k^T V_j)\\
&\times(g(\alpha U_i^T V_j+(1-\alpha)\sum_{k\in\mathcal{T}(i)} S_{ik}U_k^T V_j)-R_{ij})\\
&\times(\alpha U_i+(1-\alpha)\sum_{k\in\mathcal{T}(i)} S_{ik}U_k^T)+\lambda_V V_j,
\end{aligned}
$$

# Complexity

- In general, the complexity of this method is linear with the observations the user-item matrix

# Epinions Dataset

- 51,670 users who rated 83,509 items with totally 631,064 ratings
- Rating Density 0.015%
- The total number of issued trust statements is 511,799

# Metrics

- Mean Absolute Error and Root Mean Square Error

$$MAE = \frac{\sum_{i,j} |r_{i,j} - \widehat{r}_{i,j}|}{N}$$

$$RMSE = \sqrt{\frac{\sum_{i,j} (r_{i,j} - \widehat{r}_{i,j})^2}{N}}$$

# Comparisons

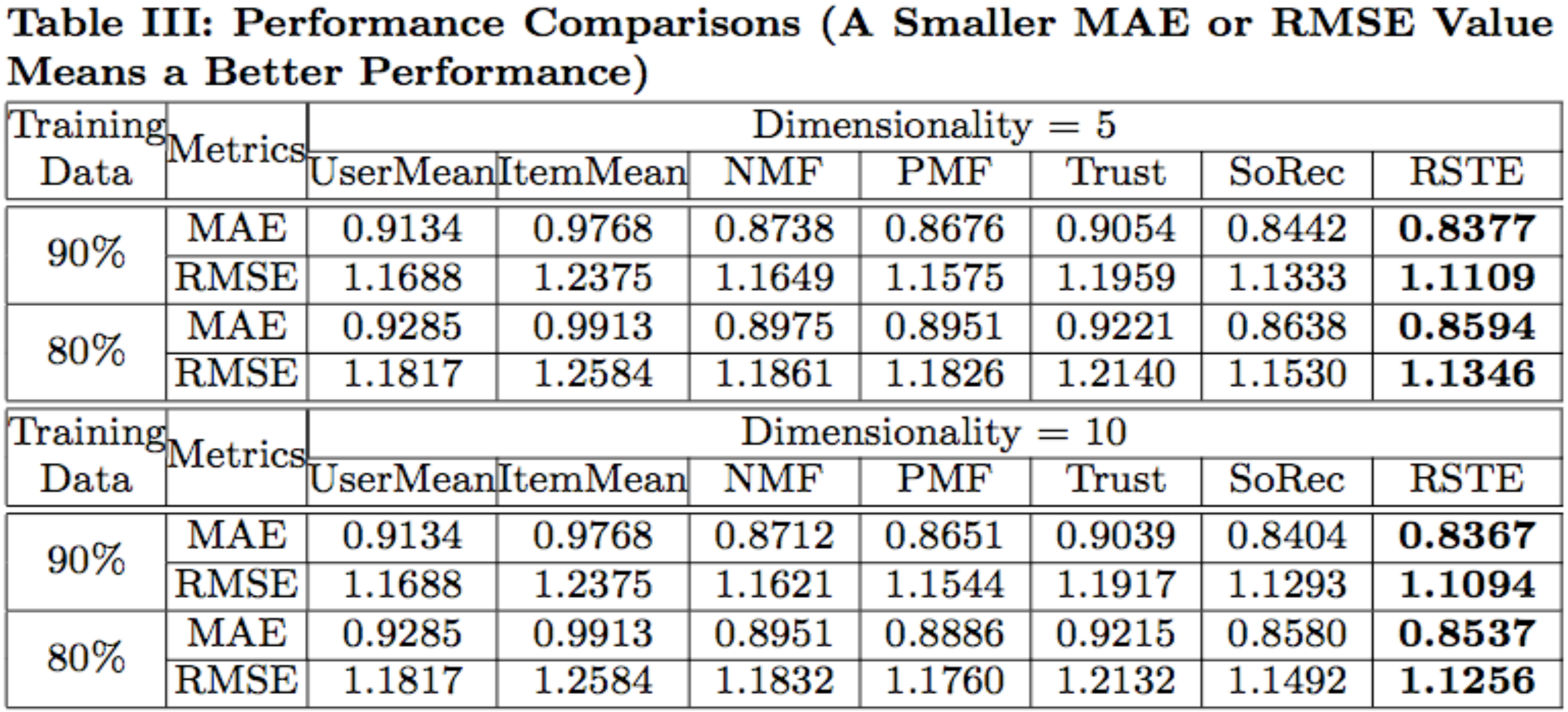


**Table III: Performance Comparisons (A Smaller MAE or RMSE Value Means a Better Performance)**

| Training Data | Metrics | Dimensionality = 5 | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | UserMean | ItemMean | NMF | PMF | Trust | SoRec | RSTE |
| 90% | MAE | 0.9134 | 0.9768 | 0.8738 | 0.8676 | 0.9054 | 0.8442 | **0.8377** |
| | RMSE | 1.1688 | 1.2375 | 1.1649 | 1.1575 | 1.1959 | 1.1333 | **1.1109** |
| 80% | MAE | 0.9285 | 0.9913 | 0.8975 | 0.8951 | 0.9221 | 0.8638 | **0.8594** |
| | RMSE | 1.1817 | 1.2584 | 1.1861 | 1.1826 | 1.2140 | 1.1530 | **1.1346** |

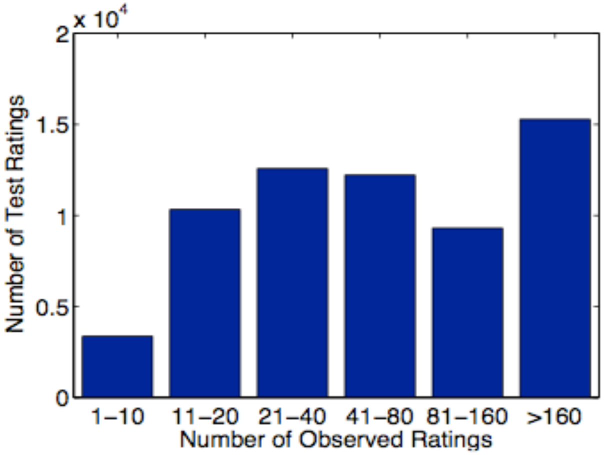
| Training Data | Metrics | Dimensionality = 10 | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | UserMean | ItemMean | NMF | PMF | Trust | SoRec | RSTE |
| 90% | MAE | 0.9134 | 0.9768 | 0.8712 | 0.8651 | 0.9039 | 0.8404 | **0.8367** |
| | RMSE | 1.1688 | 1.2375 | 1.1621 | 1.1544 | 1.1917 | 1.1293 | **1.1094** |
| 80% | MAE | 0.9285 | 0.9913 | 0.8951 | 0.8886 | 0.9215 | 0.8580 | **0.8537** |
| | RMSE | 1.1817 | 1.2584 | 1.1832 | 1.1760 | 1.2132 | 1.1492 | **1.1256** |

NMF --- D. D. Lee and H. S. Seung (Nature 1999)
PMF --- R. Salakhutdinov and A. Mnih (NIPS 2008)
SoRec --- H. Ma, H. Yang, M. R. Lyu and I. King (CIKM 2008)
Trust, RSTE --- H. Ma, I. King and M. R. Lyu (SIGIR 2009)

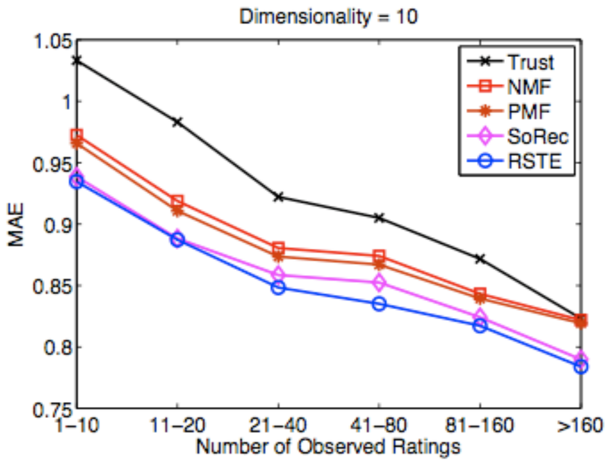
# Performance on Different Users

- Group all the users based on the number of observed ratings in the training data
- 6 classes: “1 − 10”, “11 − 20”, “21 − 40”, “41 − 80”, “81 − 160”, “> 160”,

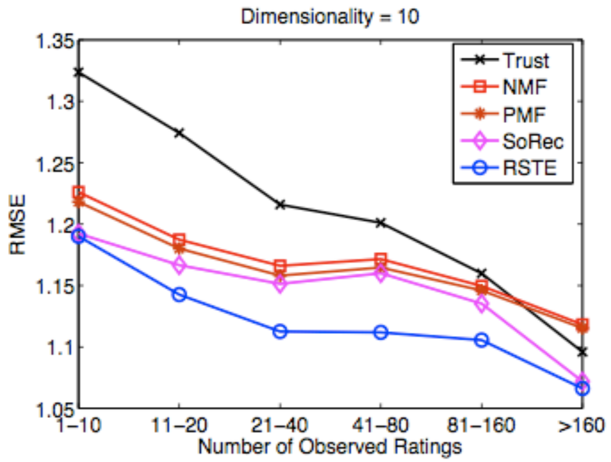
# Performance on Different Users



(a) Distribution of Testing Data (90% as Training Data)

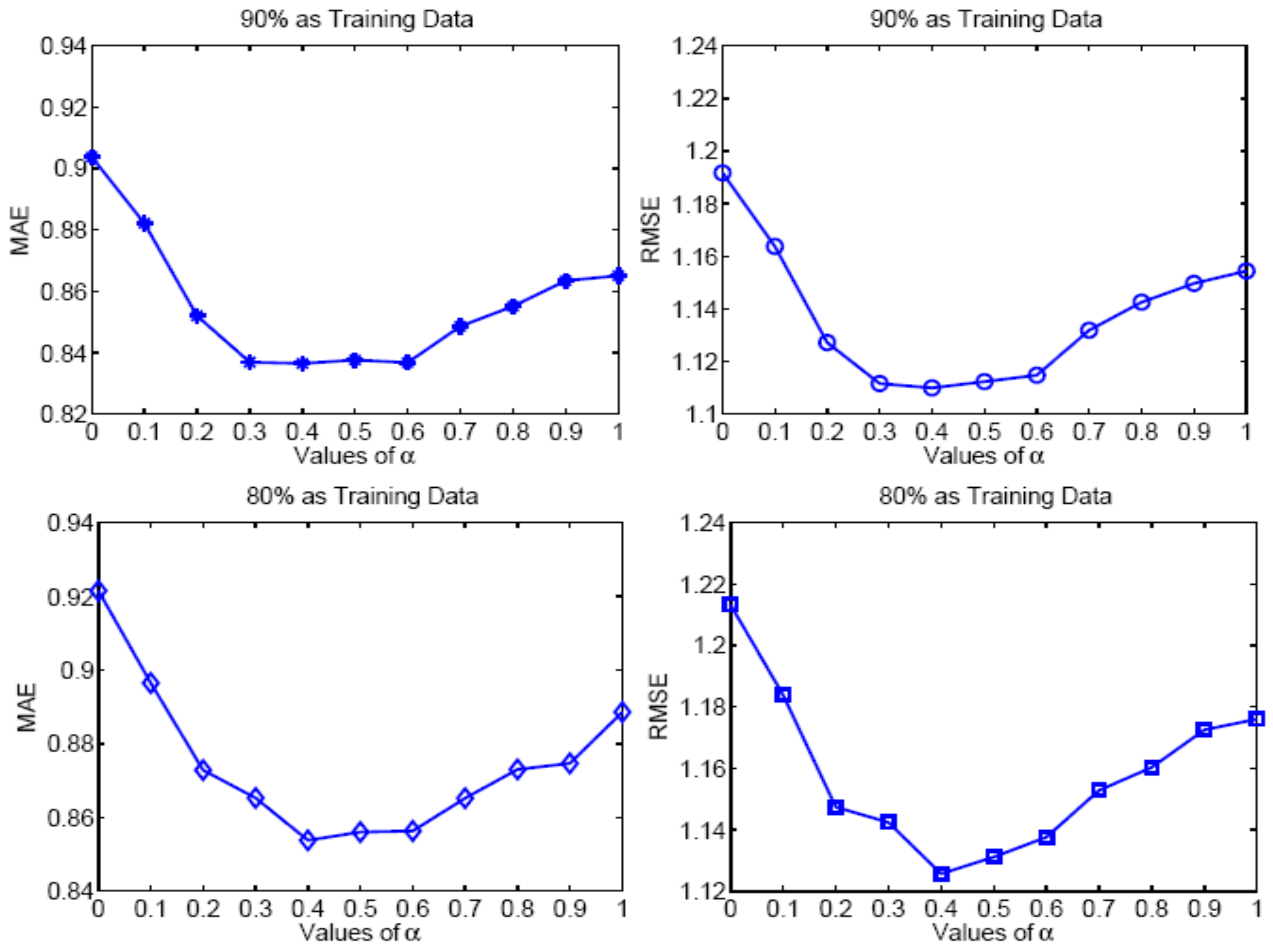


(b) MAE Comparison on Different User Rating Scales (90% as Training Data)



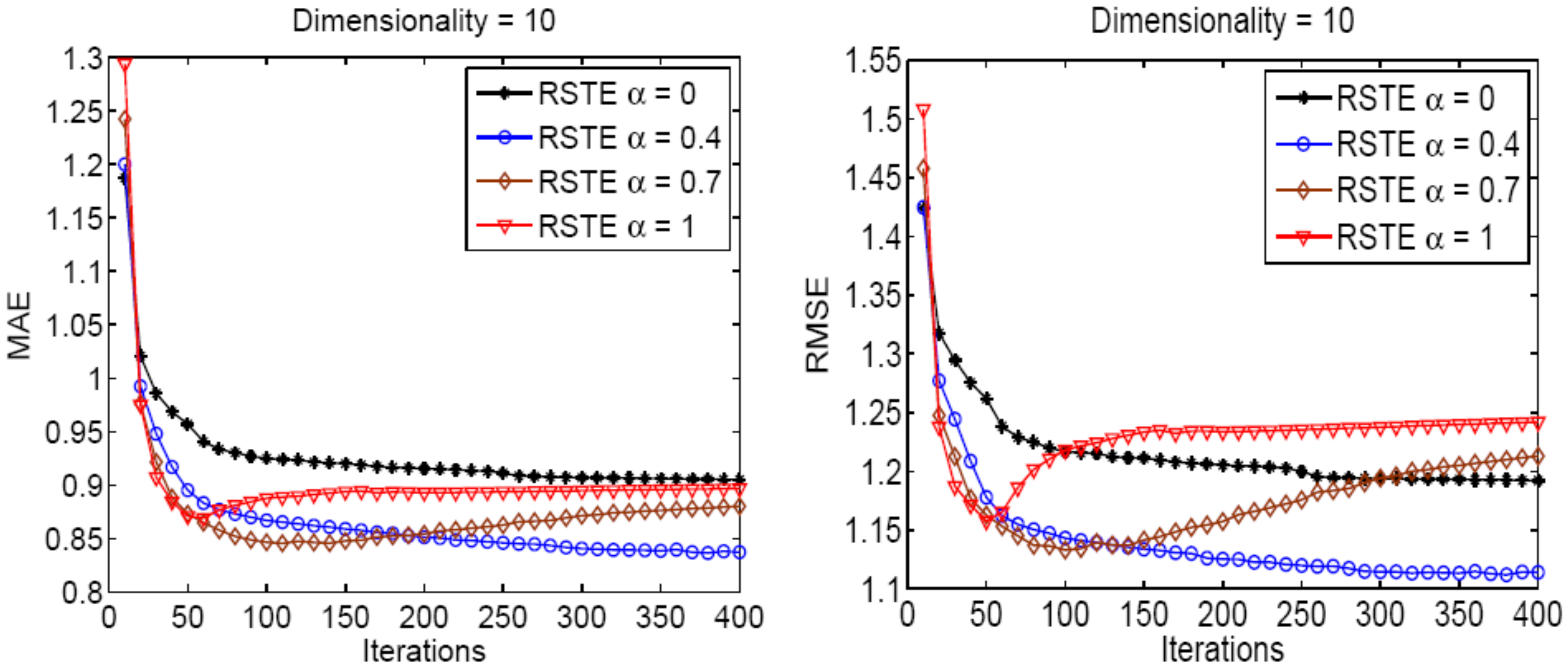
(c) RMSE Comparison on Different User Rating Scales (90% as Training Data)

# Impact of Parameter Alpha



**Impact of Parameter $\alpha$ (Dimensionality = 10)**

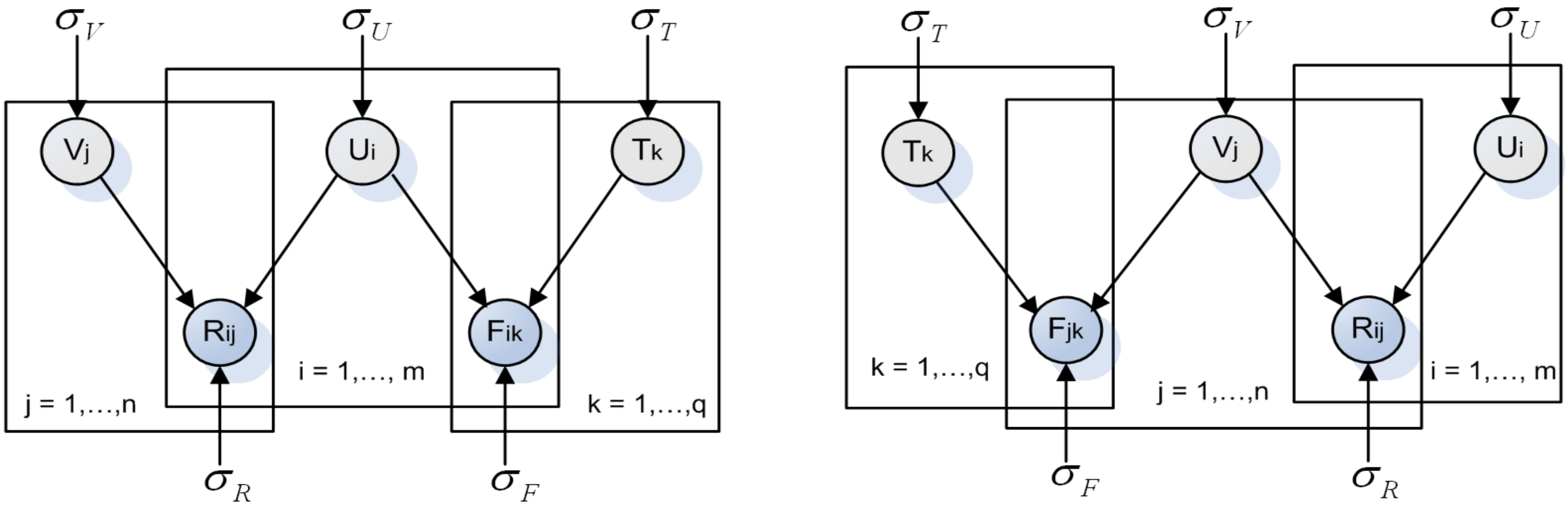
# MAE and RMSE Changes with Iterations



90% as Training Data

# Further Discussion of SoRec

- Improving Recommender Systems Using Social Tags



MovieLens Dataset

71,567 users, 10,681 movies,

10,000,054 ratings, 95,580 tags

# Further Discussion of SoRec

- MAE

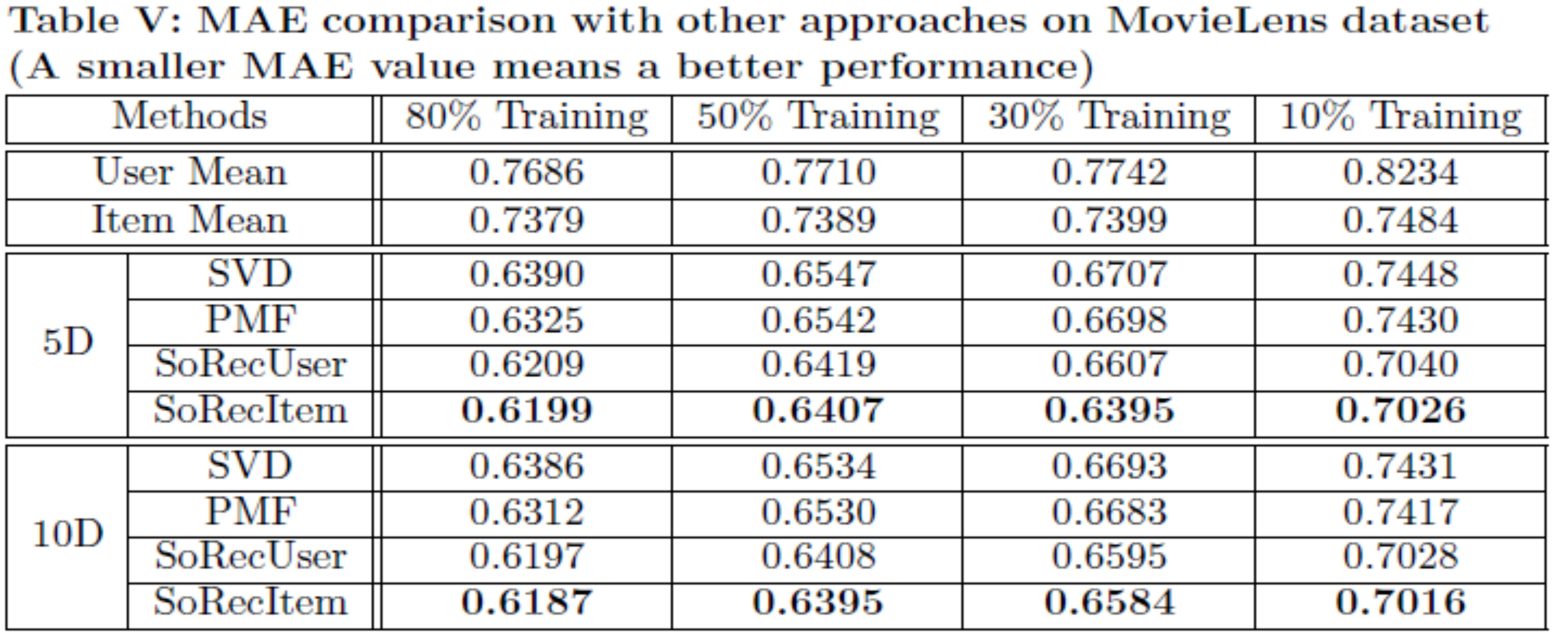


Table V: MAE comparison with other approaches on MovieLens dataset (A smaller MAE value means a better performance)

| Methods | | 80% Training | 50% Training | 30% Training | 10% Training |
|---|---|---|---|---|---|
| User Mean | | 0.7686 | 0.7710 | 0.7742 | 0.8234 |
| Item Mean | | 0.7379 | 0.7389 | 0.7399 | 0.7484 |
| 5D | SVD | 0.6390 | 0.6547 | 0.6707 | 0.7448 |
| | PMF | 0.6325 | 0.6542 | 0.6698 | 0.7430 |
| | SoRecUser | 0.6209 | 0.6419 | 0.6607 | 0.7040 |
| | SoRecItem | **0.6199** | **0.6407** | **0.6395** | **0.7026** |
| 10D | SVD | 0.6386 | 0.6534 | 0.6693 | 0.7431 |
| | PMF | 0.6312 | 0.6530 | 0.6683 | 0.7417 |
| | SoRecUser | 0.6197 | 0.6408 | 0.6595 | 0.7028 |
| | SoRecItem | **0.6187** | **0.6395** | **0.6584** | **0.7016** |

# Further Discussion of SoRec

- RMSE

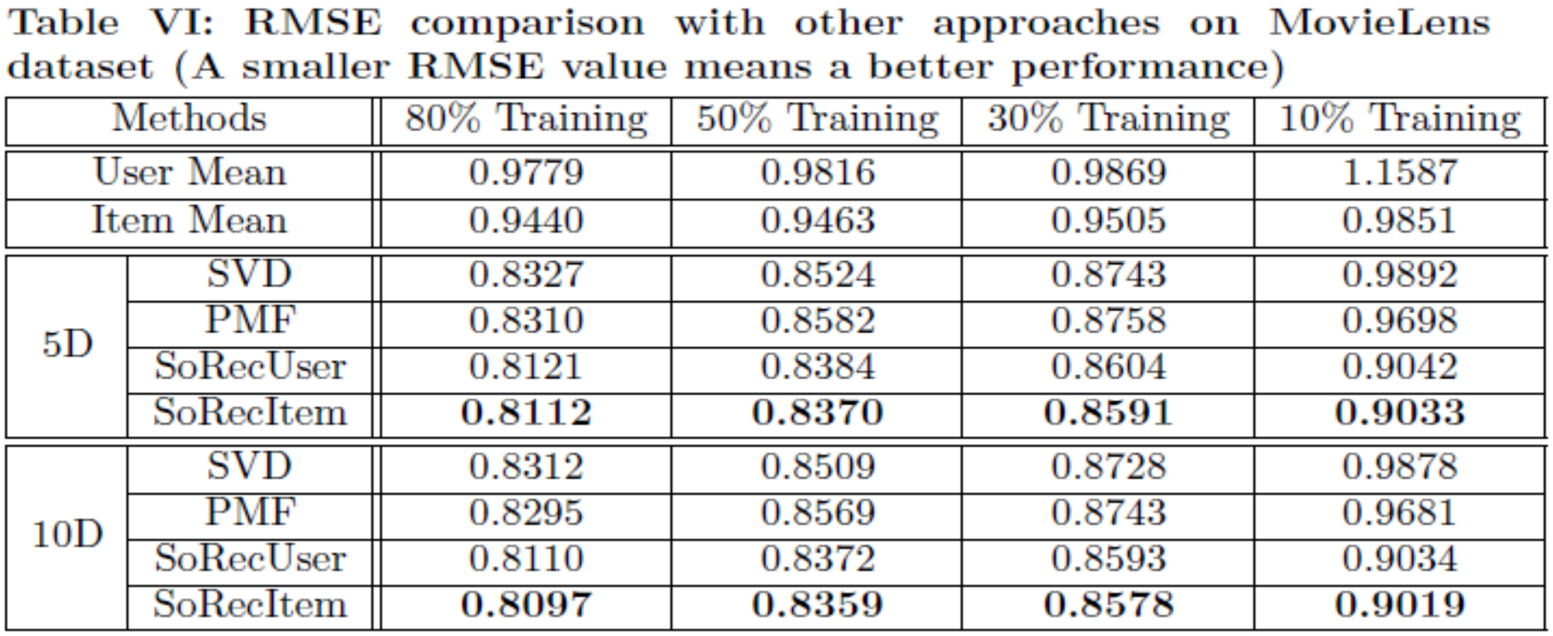
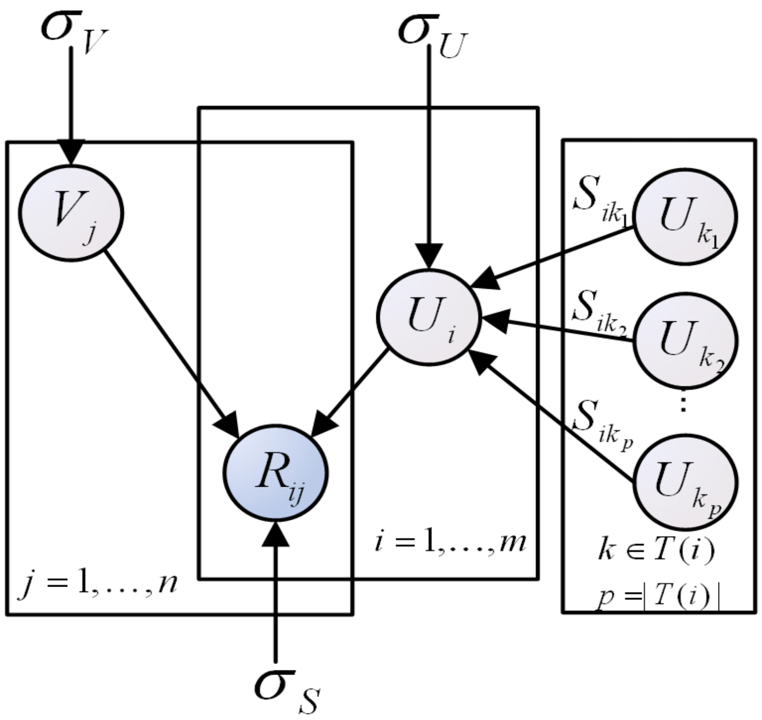


Table VI: RMSE comparison with other approaches on MovieLens dataset (A smaller RMSE value means a better performance)

| Methods | | 80% Training | 50% Training | 30% Training | 10% Training |
|---|---|---|---|---|---|
| User Mean | | 0.9779 | 0.9816 | 0.9869 | 1.1587 |
| Item Mean | | 0.9440 | 0.9463 | 0.9505 | 0.9851 |
| 5D | SVD | 0.8327 | 0.8524 | 0.8743 | 0.9892 |
| | PMF | 0.8310 | 0.8582 | 0.8758 | 0.9698 |
| | SoRecUser | 0.8121 | 0.8384 | 0.8604 | 0.9042 |
| | SoRecItem | **0.8112** | **0.8370** | **0.8591** | **0.9033** |
| 10D | SVD | 0.8312 | 0.8509 | 0.8728 | 0.9878 |
| | PMF | 0.8295 | 0.8569 | 0.8743 | 0.9681 |
| | SoRecUser | 0.8110 | 0.8372 | 0.8593 | 0.9034 |
| | SoRecItem | **0.8097** | **0.8359** | **0.8578** | **0.9019** |

# Further Discussion of RSTE

- Relationship with Neighborhood-based methods

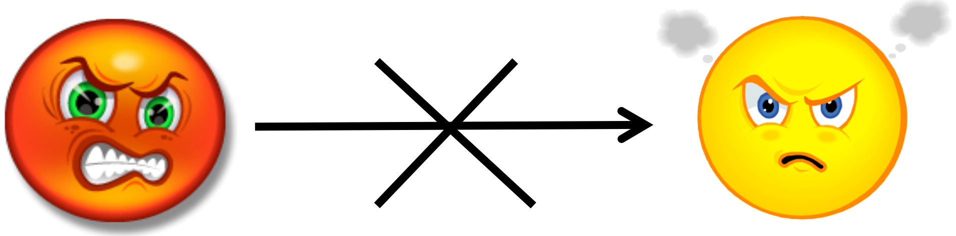


- The trusted friends are actually the explicit neighbors
- We can easily apply this method to include implicit neighbors
- Using PCC to calculate similar users for every user

# What We Cannot Model Using SoRec and RSTE?

- Propagation of trust

- Distrust



# Social Recommender Systems

- Introduction
- Collaborative Filtering
- Trust-aware Recommender Systems
- Social-based Recommender Systems
- Web Site Recommendation

# Recommend with Social Distrust

[Hao Ma, et al., RecSys2009]

# Trust vs. Social

- Trust-aware
  - Trust network: unilateral relations
  - Trust relations can be treated as “similar” relations
  - Few datasets available on the Web
- Social-based
  - Social friend network: mutual relations
  - Friends are very diverse, and may have different tastes
  - Lots of Web sites have social network implementation

# Distrust

- Users' distrust relations can be interpreted as the "dissimilar" relations
  - On the web, user $U_i$ distrusts user $U_d$ indicates that user $U_i$ disagrees with most of the opinions issued by user $U_d$.
  - What to do if a user distrusts many people?
  - What to do if many people distrust a user?

# Distrust

$$\boxed{\max_{U} \frac{1}{2}} \sum_{i=1}^{m} \sum_{d \in \mathcal{D}^{+}(i)} S_{id}^{\mathcal{D}} \| U_i - U_d \|_F^2$$

$$\begin{aligned}
\min_{U,V} \mathcal{L}_{\mathcal{D}}(R, S^{\mathcal{D}}, U, V) &= \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{n} I_{ij}^{R} (R_{ij} - g(U_i^T V_j))^2 \\
&+ \frac{\beta}{2} \sum_{i=1}^{m} \sum_{d \in \mathcal{D}^{+}(i)} \boxed{(-S_{id}^{\mathcal{D}} \| U_i - U_d \|_F^2)} \\
&+ \frac{\lambda_U}{2} \|U\|_F^2 + \frac{\lambda_V}{2} \|V\|_F^2 .
\end{aligned}$$

# Trust

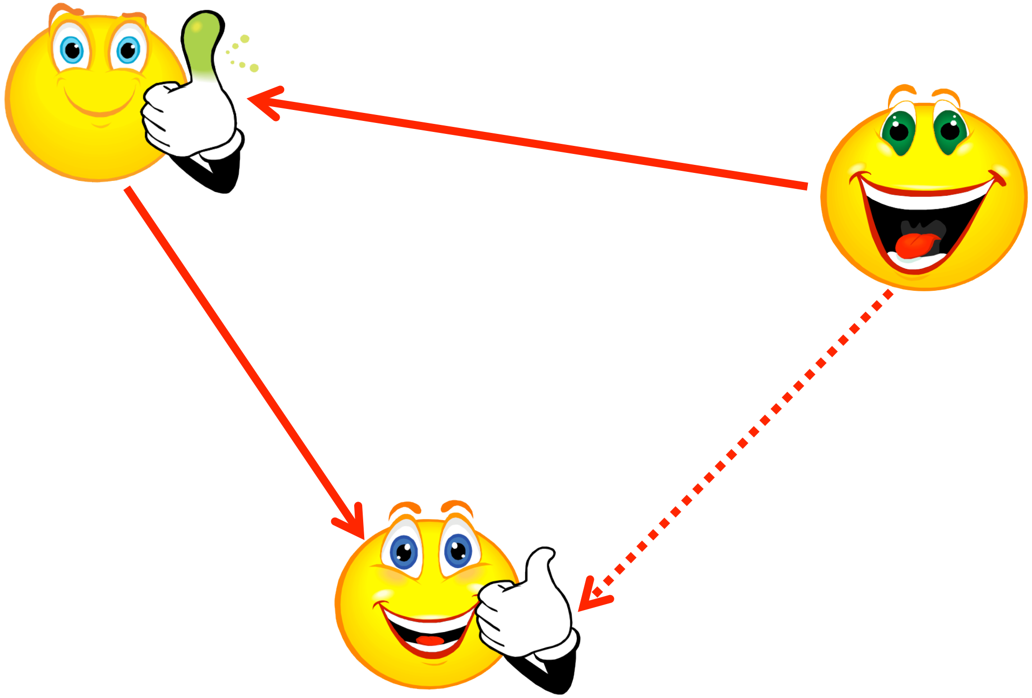
- Users' trust relations can be interpreted as the "similar" relations
  - On the web, user $U_i$ trusts user $U_t$ indicates that user $U_i$ agrees with most of the opinions issued by user $U_t$.

# Trust

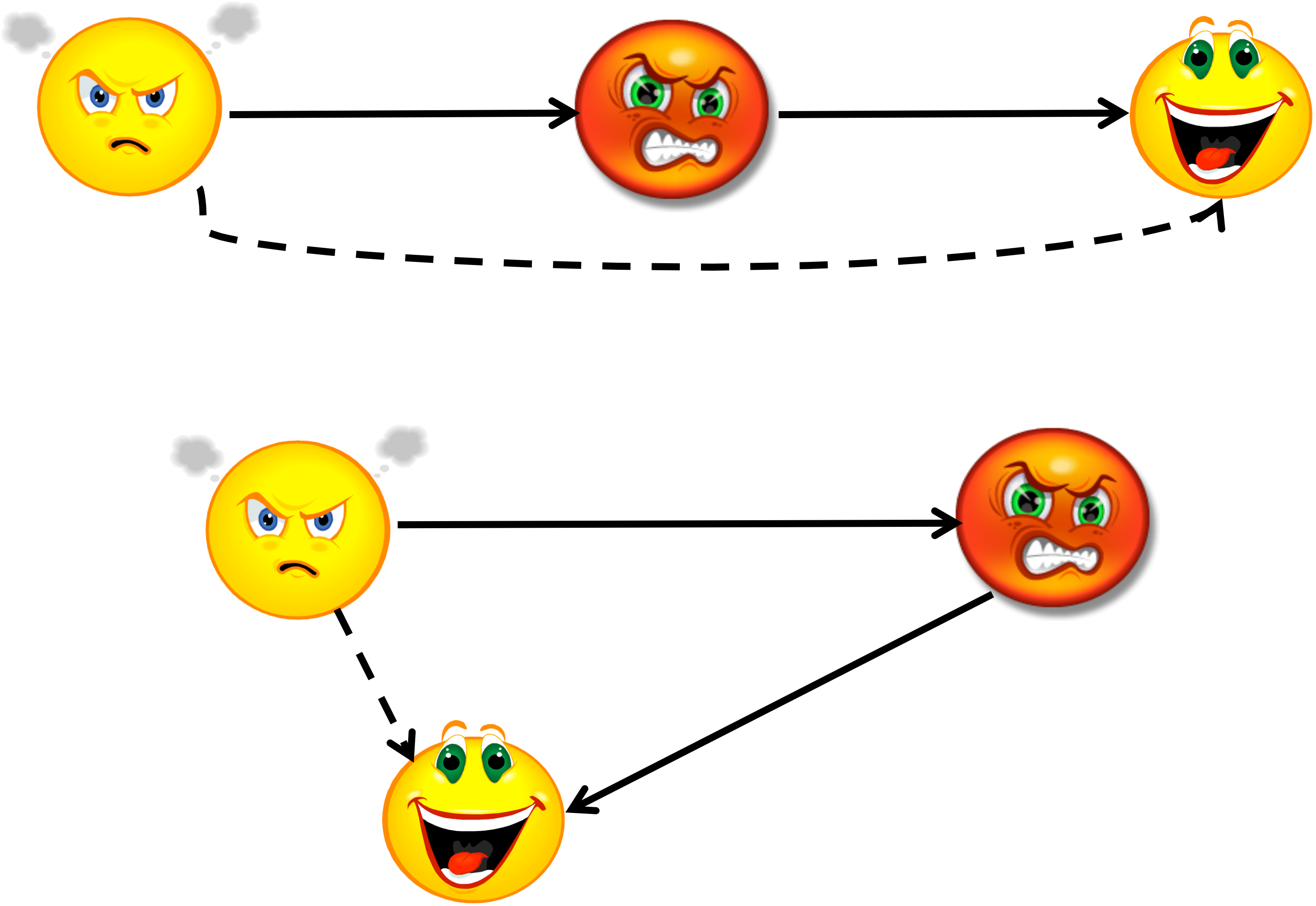
$$\boxed{\min_{U}} \frac{1}{2} \sum_{i=1}^{m} \sum_{t \in \mathcal{T}^{+}(i)} S_{it}^{\mathcal{T}} \|U_i - U_t\|_F^2$$

$$\begin{aligned}
\min_{U,V} \mathcal{L}_{\mathcal{T}}(R, S^{\mathcal{T}}, U, V) &= \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{n} I_{ij}^{R} (R_{ij} - g(U_i^T V_j))^2 \\
&+ \frac{\alpha}{2} \sum_{i=1}^{m} \sum_{t \in \mathcal{T}^{+}(i)} \boxed{(S_{it}^{\mathcal{T}} \|U_i - U_t\|_F^2)} \\
&+ \frac{\lambda_U}{2} \|U\|_F^2 + \frac{\lambda_V}{2} \|V\|_F^2 .
\end{aligned}$$

# Trust Propagation



# Distrust Propagation?



# Experiments

- Dataset - Epinions
- 131,580 users, 755,137 items, 13,430,209 ratings
- 717,129 trust relations, 123,670 distrust relations

# Data Statistics

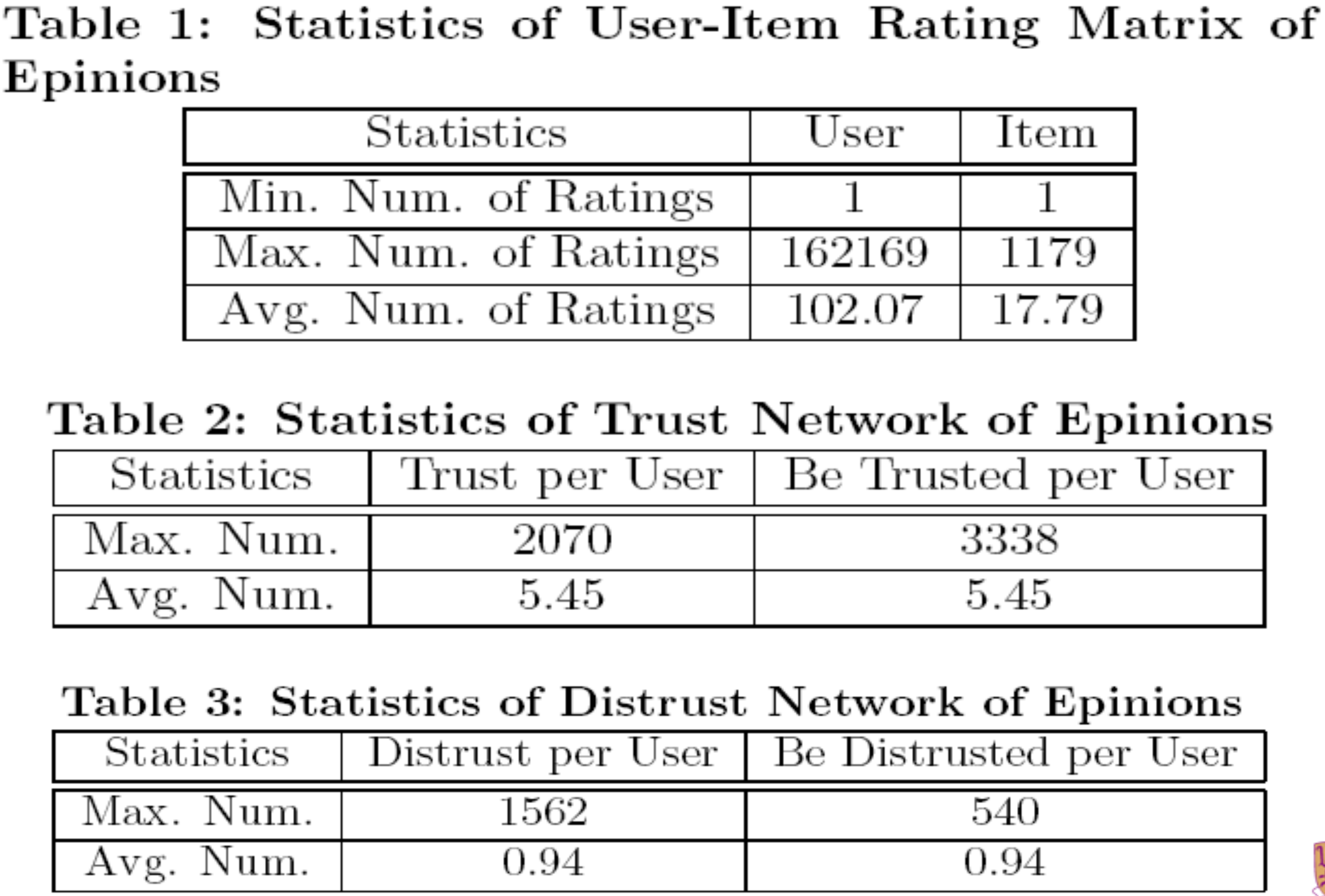


Table 1: Statistics of User-Item Rating Matrix of Epinions

| Statistics | User | Item |
|---|---|---|
| Min. Num. of Ratings | 1 | 1 |
| Max. Num. of Ratings | 162169 | 1179 |
| Avg. Num. of Ratings | 102.07 | 17.79 |

Table 2: Statistics of Trust Network of Epinions

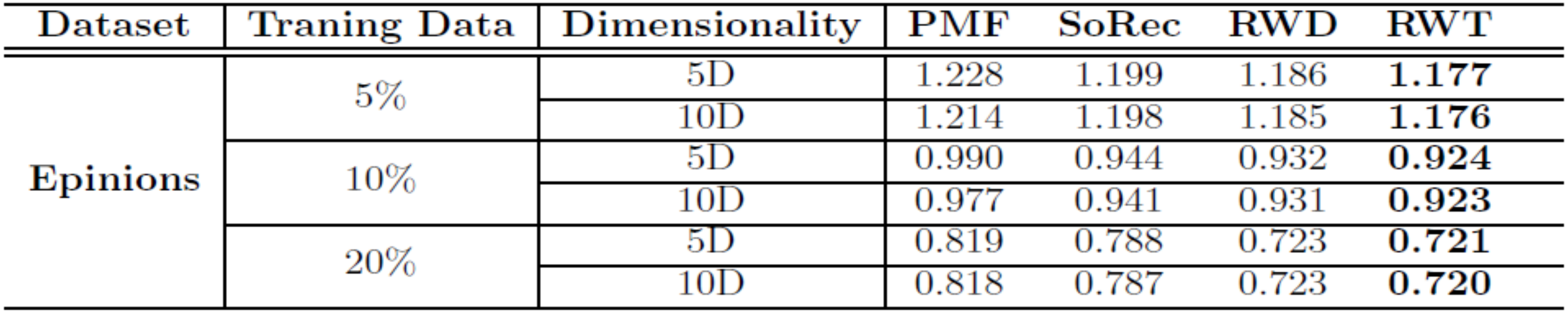
| Statistics | Trust per User | Be Trusted per User |
|---|---|---|
| Max. Num. | 2070 | 3338 |
| Avg. Num. | 5.45 | 5.45 |

Table 3: Statistics of Distrust Network of Epinions

| Statistics | Distrust per User | Be Distrusted per User |
|---|---|---|
| Max. Num. | 1562 | 540 |
| Avg. Num. | 0.94 | 0.94 |

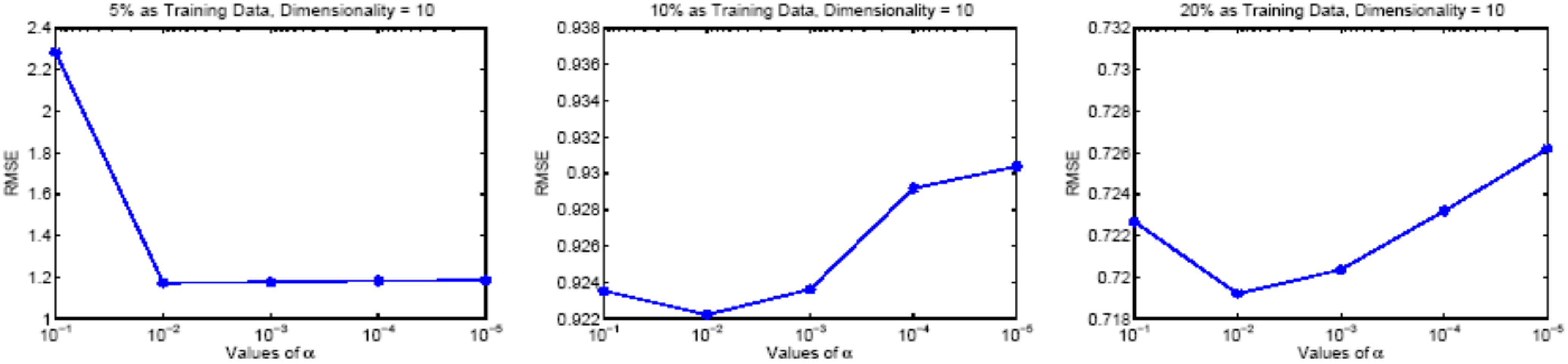
# Experiments

## RMSE



| Dataset | Traning Data | Dimensionality | PMF | SoRec | RWD | RWT |
|---|---|---|---|---|---|---|
| **Epinions** | 5% | 5D | 1.228 | 1.199 | 1.186 | **1.177** |
| | | 10D | 1.214 | 1.198 | 1.185 | **1.176** |
| | 10% | 5D | 0.990 | 0.944 | 0.932 | **0.924** |
| | | 10D | 0.977 | 0.941 | 0.931 | **0.923** |
| | 20% | 5D | 0.819 | 0.788 | 0.723 | **0.721** |
| | | 10D | 0.818 | 0.787 | 0.723 | **0.720** |

# Impact of Parameters



(a) 5% as Training Data (b) 10% as Training Data (c) 20% as Training Data

**Figure 6: Impact of Parameter $\alpha$**

Alpha = 0.01 will get the best performance!

Parameter beta basically shares the same trend!

# Social Recommender Systems

- Introduction
- Collaborative Filtering
- Trust-aware Recommender Systems
- Social-based Recommender Systems

# Comparison

- Trust-aware Recommender systems
  - Trust network
  - Trust relations can be treated as “similar” relations
  - Few dataset available on the web
- Social-based Recommender Systems
  - Social friend network, mutual relations
  - Friends are very divers, and may have different tastes
  - Lots of web sites have social network implementation

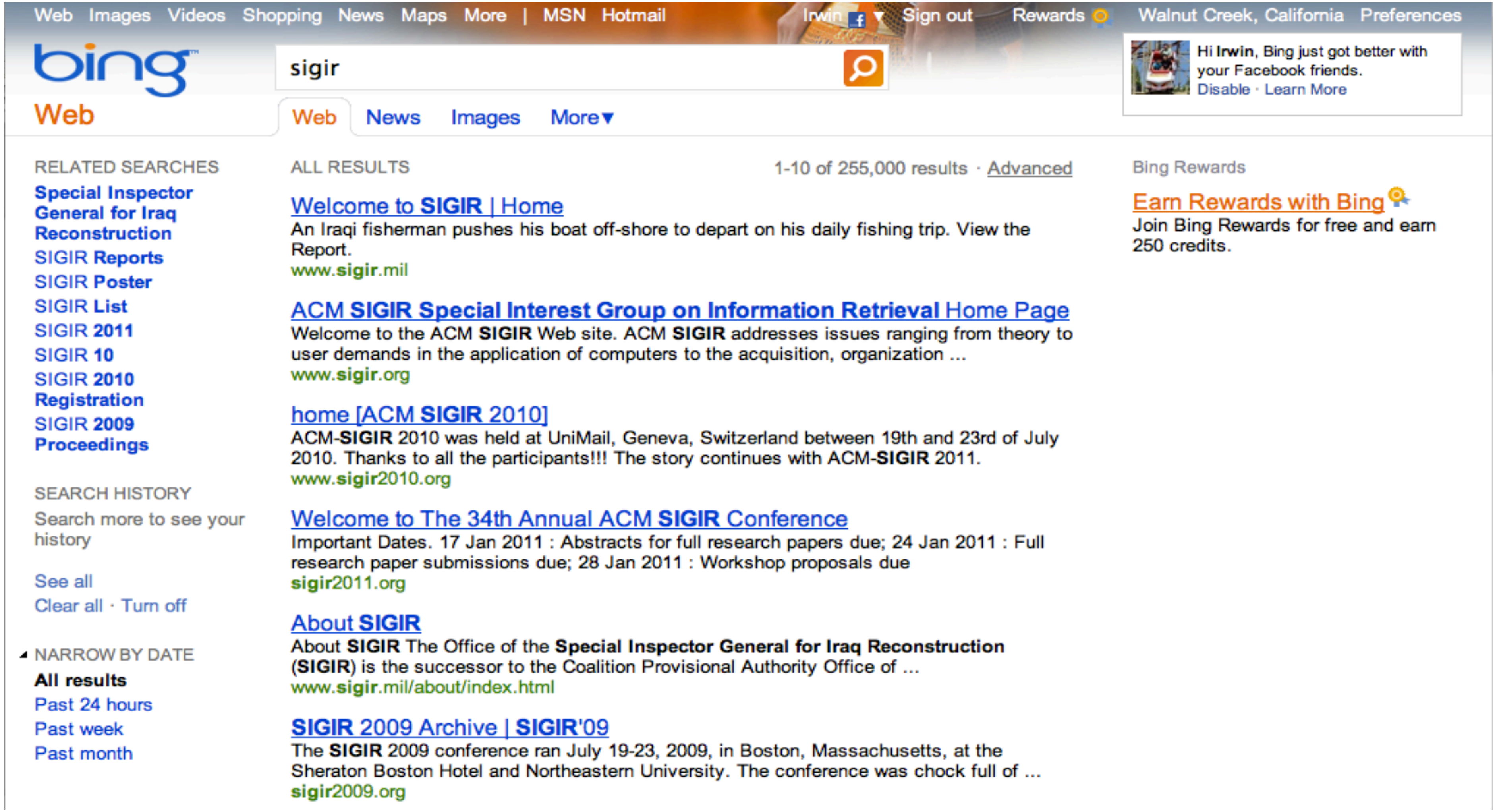
# Social Recommender Systems

- Introduction
- Collaborative Filtering
- Trust-aware Recommender Systems
- Social-based Recommender Systems
- Web Site Recommendation

# Web Site Recommendation

[Ma et al., SIGIR 2011]

# Traditional Search Paradigm



Hi **Irwin**, Bing just got better with your Facebook friends.

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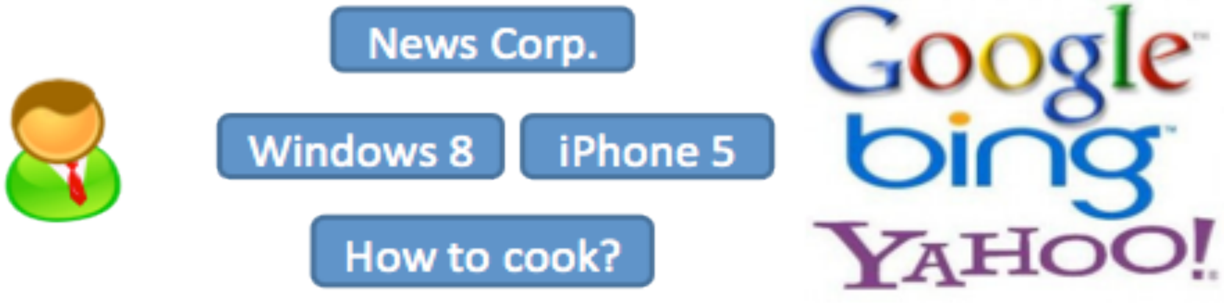

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# Challenges

- Infeasible to ask Web users to explicitly rate Web site
- Not all the traditional methods can be directly applied to the Web site recommendation task
- Can only take advantages of implicit user behavior data

# Motivations

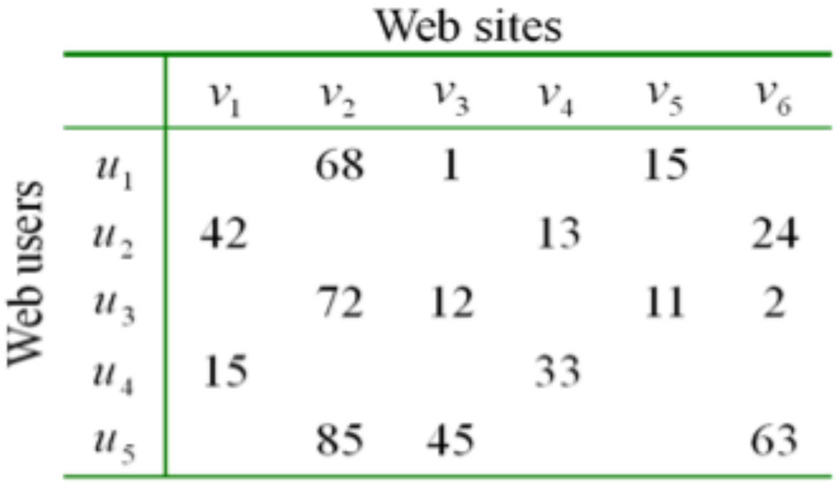
- A Web user’s preference can be represented by how frequently a user visits each site

- Higher visiting frequency on a site means heavy information needs while lower frequency indicates less interests

- User-query issuing frequency data can be used to refine a user’s preference

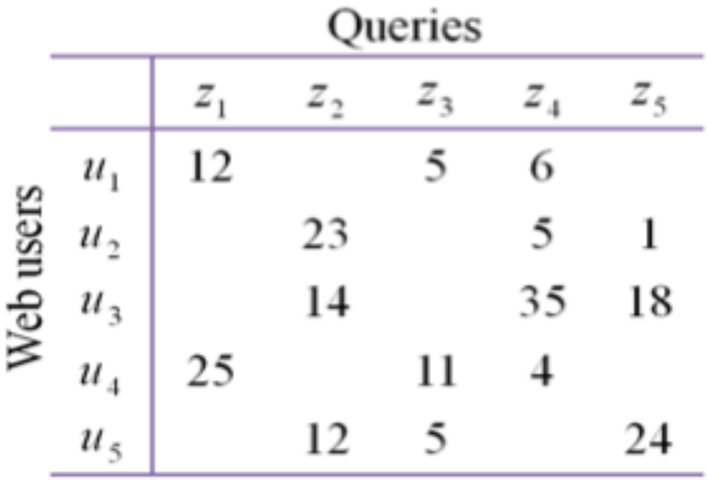
# Using Clicks as Ratings

| ID | Query | URL |
|---|---|---|
| 358 | facebook | http://www.facebook.com |
| 358 | rww | http://www.readwriteweb.com |
| 3968 | iphone4 | http://www.apple.com |
| 3968 | ipad | http://www.apple.com |
| ... | ... | ... |



Web sites

| Web users | | $v_1$ | $v_2$ | $v_3$ | $v_4$ | $v_5$ | $v_6$ |
|---|---|---|---|---|---|---|---|
| | $u_1$ | | 68 | 1 | | 15 | |
| | $u_2$ | 42 | | | 13 | | 24 |
| | $u_3$ | | 72 | 12 | | 11 | 2 |
| | $u_4$ | 15 | | | 33 | | |
| | $u_5$ | | 85 | 45 | | | 63 |



Queries

| Web users | | $z_1$ | $z_2$ | $z_3$ | $z_4$ | $z_5$ |
|---|---|---|---|---|---|---|
| | $u_1$ | 12 | | 5 | 6 | |
| | $u_2$ | | 23 | | 5 | 1 |
| | $u_3$ | | 14 | | 35 | 18 |
| | $u_4$ | 25 | | 11 | 4 | |
| | $u_5$ | | 12 | 5 | | 24 |

# Matrix Factorization

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

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

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

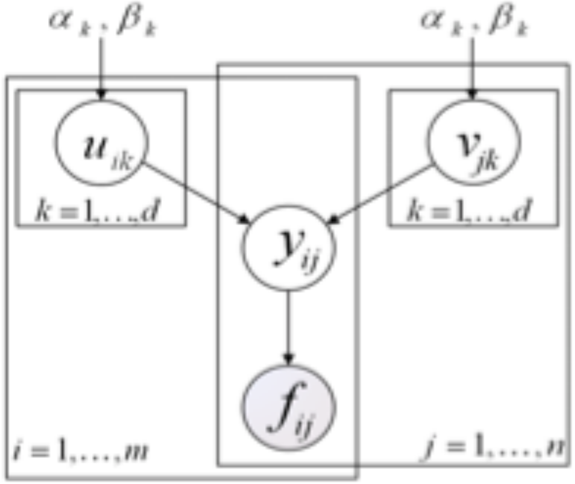
$$p(V|\sigma_V^2)=\prod_{j=1}^{n}\mathcal{N}(V_j|0,\sigma_V^2\mathbf{I})$$

# Probabilistic Factor Model

- GaP [Canny, SIGIR 2004]
  - Linear topic model

- NMF
  - No Gamma distribution on X

# Probabilistic Factor Model



1. Generate $u_{ik} \sim \text{Gamma}(\alpha_k, \beta_k), \forall k$.
2. Generate $v_{jk} \sim \text{Gamma}(\alpha_k, \beta_k), \forall k$.
3. Generate $y_{ij}$ occurrences of item or event $j$ from user $i$ with outcome $y_{ij} = \sum_{k=1}^{d} u_{ik} v_{jk}$.
4. Generate $f_{ij} \sim \text{Poisson}(y_{ij})$.

$$p(U|\boldsymbol{\alpha}, \boldsymbol{\beta}) = \prod_{i=1}^{m} \prod_{k=1}^{d} \frac{u_{ik}^{\alpha_k - 1} \exp(-u_{ik}/\beta_k)}{\beta_k^{\alpha_k} \Gamma(\alpha_k)}$$

$$p(V|\boldsymbol{\alpha}, \boldsymbol{\beta}) = \prod_{j=1}^{n} \prod_{k=1}^{d} \frac{v_{jk}^{\alpha_k - 1} \exp(-v_{jk}/\beta_k)}{\beta_k^{\alpha_k} \Gamma(\alpha_k)}$$

$$p(F|Y) = \prod_{i=1}^{m} \prod_{j=1}^{n} \frac{y_{ij}^{f_{ij}} \exp(-y_{ij})}{f_{ij}!}$$

$$p(U, V|F, \boldsymbol{\alpha}, \boldsymbol{\beta}) \propto p(F|Y) p(U|\boldsymbol{\alpha}, \boldsymbol{\beta}) p(V|\boldsymbol{\alpha}, \boldsymbol{\beta})$$

$$\begin{aligned}\mathcal{L}(U, V; F) \quad = \quad & \sum_{i=1}^{m} \sum_{k=1}^{d} ((\alpha_k - 1) \ln(u_{ik}/\beta_k) - u_{ik}/\beta_k) \\ & + \sum_{j=1}^{n} \sum_{k=1}^{d} ((\alpha_k - 1) \ln(v_{jk}/\beta_k) - v_{jk}/\beta_k) \\ & + \sum_{i=1}^{m} \sum_{j=1}^{n} (f_{ij} \ln y_{ij} - y_{ij}) + \text{const}.\end{aligned}$$

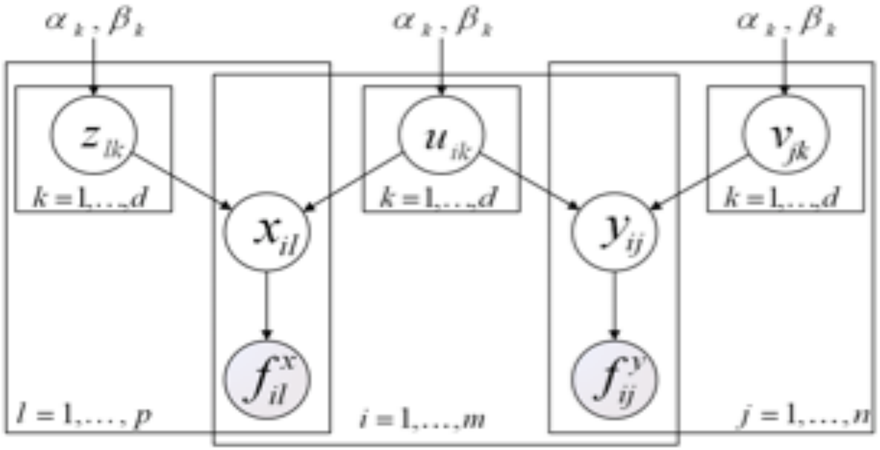
# Probabilistic Factor Model

$$
\begin{aligned}
\mathcal{L}(U,V;F) \;=\; & \sum_{i=1}^{m}\sum_{k=1}^{d}((\alpha_k-1)\ln(u_{ik}/\beta_k)-u_{ik}/\beta_k) \\
& +\sum_{j=1}^{n}\sum_{k=1}^{d}((\alpha_k-1)\ln(v_{jk}/\beta_k)-v_{jk}/\beta_k) \\
& +\sum_{i=1}^{m}\sum_{j=1}^{n}(f_{ij}\ln y_{ij}-y_{ij})+\text{const.}
\end{aligned}
$$

$$
u_{ik} \leftarrow u_{ik}\frac{\sum_{j=1}^{n}(f_{ij}v_{jk}/y_{ij})+(\alpha_k-1)/u_{ik}}{\sum_{j=1}^{n}v_{jk}+1/\beta_k}
$$

$$
v_{jk} \leftarrow v_{jk}\frac{\sum_{i=1}^{m}(f_{ij}u_{ik}/y_{ij})+(\alpha_k-1)/v_{jk}}{\sum_{i=1}^{m}u_{ik}+1/\beta_k}
$$

# Collective Probabilistic Factor Model



$$
\begin{aligned}
&\mathcal{L}(U,V,Z;F^x,F^y) \\
&= \sum_{i=1}^{m}\sum_{l=1}^{p}(f^x_{il}\ln x_{il} - x_{il}) + \sum_{i=1}^{m}\sum_{j=1}^{n}(f^y_{ij}\ln y_{ij} - y_{ij}) \\
&+ \sum_{i=1}^{m}\sum_{k=1}^{d}((\alpha_k - 1)\ln(u_{ik}/\beta_k) - u_{ik}/\beta_k) \\
&+ \sum_{j=1}^{n}\sum_{k=1}^{d}((\alpha_k - 1)\ln(v_{jk}/\beta_k) - v_{jk}/\beta_k) \\
&+ \sum_{l=1}^{p}\sum_{k=1}^{d}((\alpha_k - 1)\ln(z_{lk}/\beta_k) - z_{lk}/\beta_k) + \text{const.}
\end{aligned}
$$

$$
u_{ik} \leftarrow u_{ik}\frac{\sum_{j=1}^{n}(f^y_{ij}v_{jk}/y_{ij}) + \sum_{l=1}^{p}(f^x_{il}z_{lk}/x_{il}) + (\alpha_k - 1)/u_{ik}}{\sum_{j=1}^{n}v_{jk} + \sum_{l=1}^{p}z_{lk} + 1/\beta_k}
$$

$$
v_{jk} \leftarrow v_{jk}\frac{\sum_{i=1}^{m}(f^y_{ij}u_{ik}/y_{ij}) + (\alpha_k - 1)/v_{jk}}{\sum_{i=1}^{m}u_{ik} + 1/\beta_k},
$$

$$
z_{lk} \leftarrow z_{lk}\frac{\sum_{i=1}^{m}(f^x_{il}u_{ik}/x_{il}) + (\alpha_k - 1)/z_{lk}}{\sum_{i=1}^{m}u_{ik} + 1/\beta_k}.
$$

$$
u_{ik}\leftarrow u_{ik}\frac{\theta\sum_{j=1}^{n}(f^y_{ij}v_{jk}/y_{ij}) + (1-\theta)\sum_{l=1}^{p}(f^x_{il}z_{lk}/x_{il}) + (\alpha_k - 1)/u_{ik}}{\theta\sum_{j=1}^{n}v_{jk} + (1-\theta)\sum_{l=1}^{p}z_{lk} + 1/\beta_k}
$$

# Dataset

- Anonymous logs of Web sites visited by users who opted-in to provide data through browser toolbar
- URLs of all the Web sites are truncated to the site level
- After pruning one month data, we have 165,403 users, 265,367 URLs and 442,598 queries
- User-site frequency matrix has 2,612,016 entries, while in user-query frequency matrix has 833,581 entries

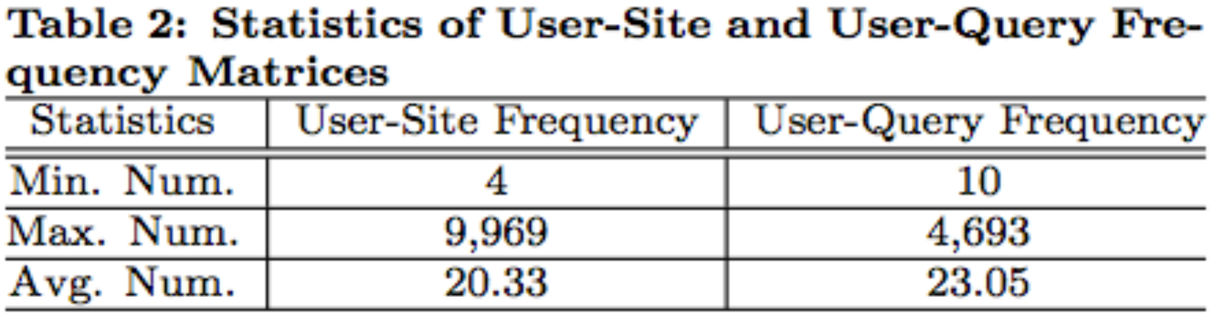


**Table 2: Statistics of User-Site and User-Query Frequency Matrices**

| Statistics | User-Site Frequency | User-Query Frequency |
|---|---|---|
| Min. Num. | 4 | 10 |
| Max. Num. | 9,969 | 4,693 |
| Avg. Num. | 20.33 | 23.05 |

# Performance Comparison

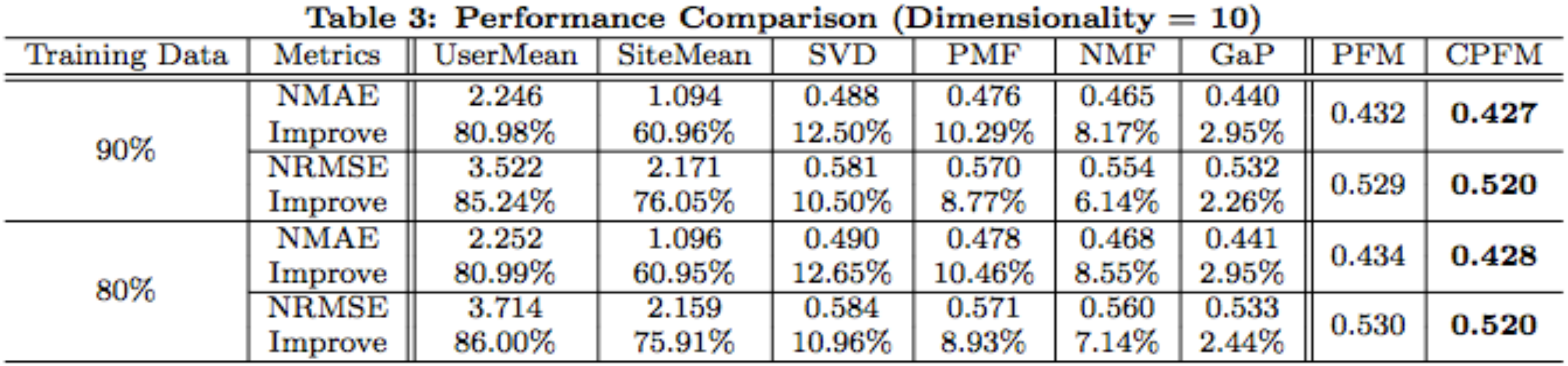


Table 3: Performance Comparison (Dimensionality = 10)

| Training Data | Metrics | UserMean | SiteMean | SVD | PMF | NMF | GaP | PFM | CPFM |
|---|---|---|---|---|---|---|---|---|---|
| 90% | NMAE | 2.246 | 1.094 | 0.488 | 0.476 | 0.465 | 0.440 | 0.432 | **0.427** |
| | Improve | 80.98% | 60.96% | 12.50% | 10.29% | 8.17% | 2.95% | | |
| | NRMSE | 3.522 | 2.171 | 0.581 | 0.570 | 0.554 | 0.532 | 0.529 | **0.520** |
| | Improve | 85.24% | 76.05% | 10.50% | 8.77% | 6.14% | 2.26% | | |
| 80% | NMAE | 2.252 | 1.096 | 0.490 | 0.478 | 0.468 | 0.441 | 0.434 | **0.428** |
| | Improve | 80.99% | 60.95% | 12.65% | 10.46% | 8.55% | 2.95% | | |
| | NRMSE | 3.714 | 2.159 | 0.584 | 0.571 | 0.560 | 0.533 | 0.530 | **0.520** |
| | Improve | 86.00% | 75.91% | 10.96% | 8.93% | 7.14% | 2.44% | | |

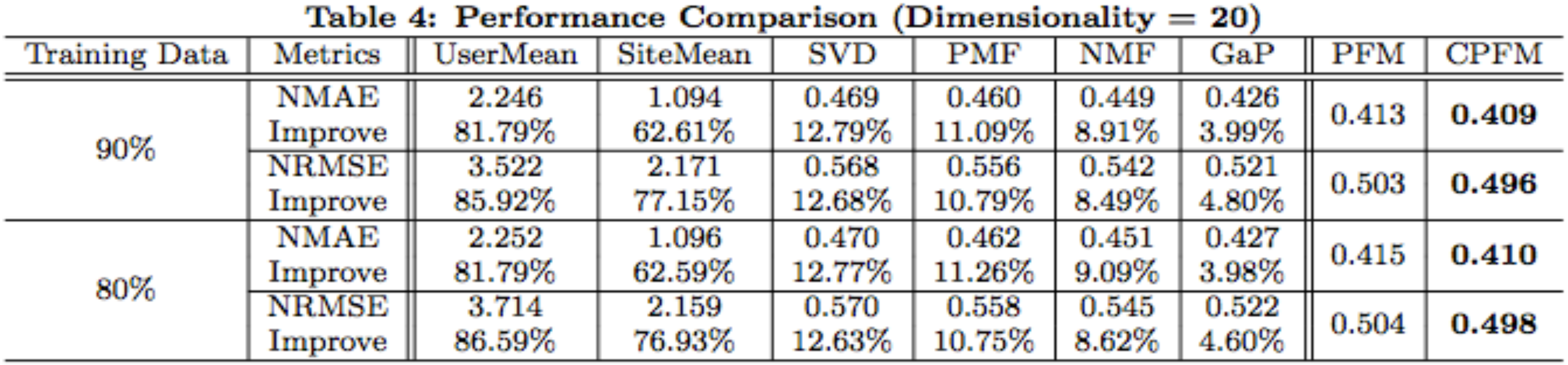
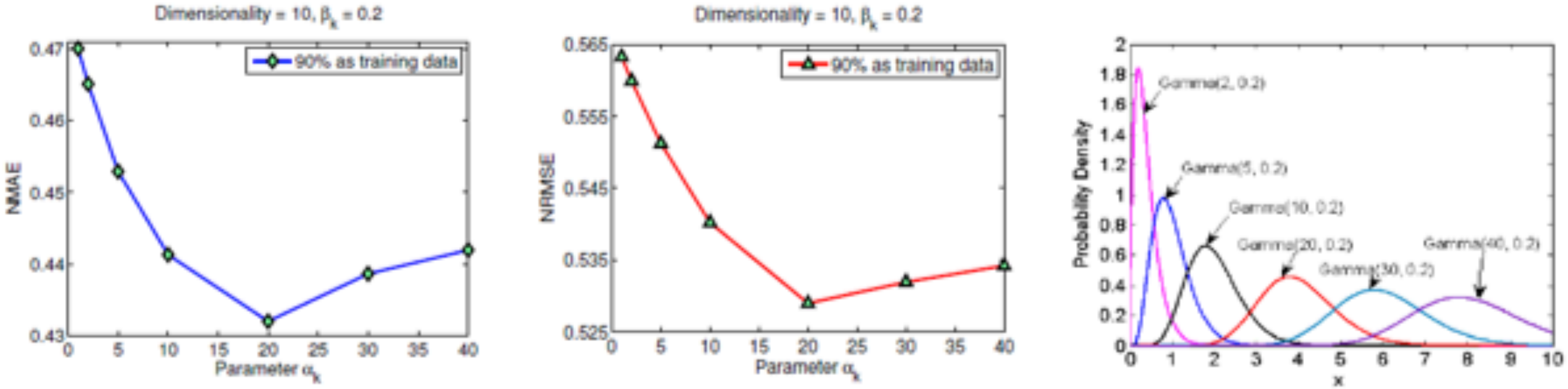


Table 4: Performance Comparison (Dimensionality = 20)

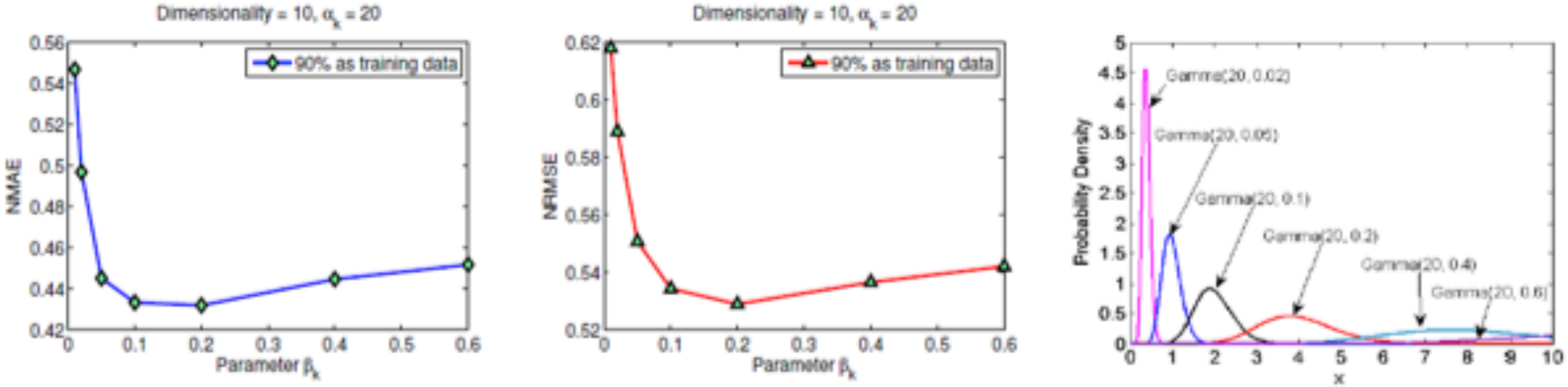
| Training Data | Metrics | UserMean | SiteMean | SVD | PMF | NMF | GaP | PFM | CPFM |
|---|---|---|---|---|---|---|---|---|---|
| 90% | NMAE | 2.246 | 1.094 | 0.469 | 0.460 | 0.449 | 0.426 | 0.413 | **0.409** |
| | Improve | 81.79% | 62.61% | 12.79% | 11.09% | 8.91% | 3.99% | | |
| | NRMSE | 3.522 | 2.171 | 0.568 | 0.556 | 0.542 | 0.521 | 0.503 | **0.496** |
| | Improve | 85.92% | 77.15% | 12.68% | 10.79% | 8.49% | 4.80% | | |
| 80% | NMAE | 2.252 | 1.096 | 0.470 | 0.462 | 0.451 | 0.427 | 0.415 | **0.410** |
| | Improve | 81.79% | 62.59% | 12.77% | 11.26% | 9.09% | 3.98% | | |
| | NRMSE | 3.714 | 2.159 | 0.570 | 0.558 | 0.545 | 0.522 | 0.504 | **0.498** |
| | Improve | 86.59% | 76.93% | 12.63% | 10.75% | 8.62% | 4.60% | | |

# Impact of Parameters



(a) NMAE (b) NRMSE (c) Gamma Distributions

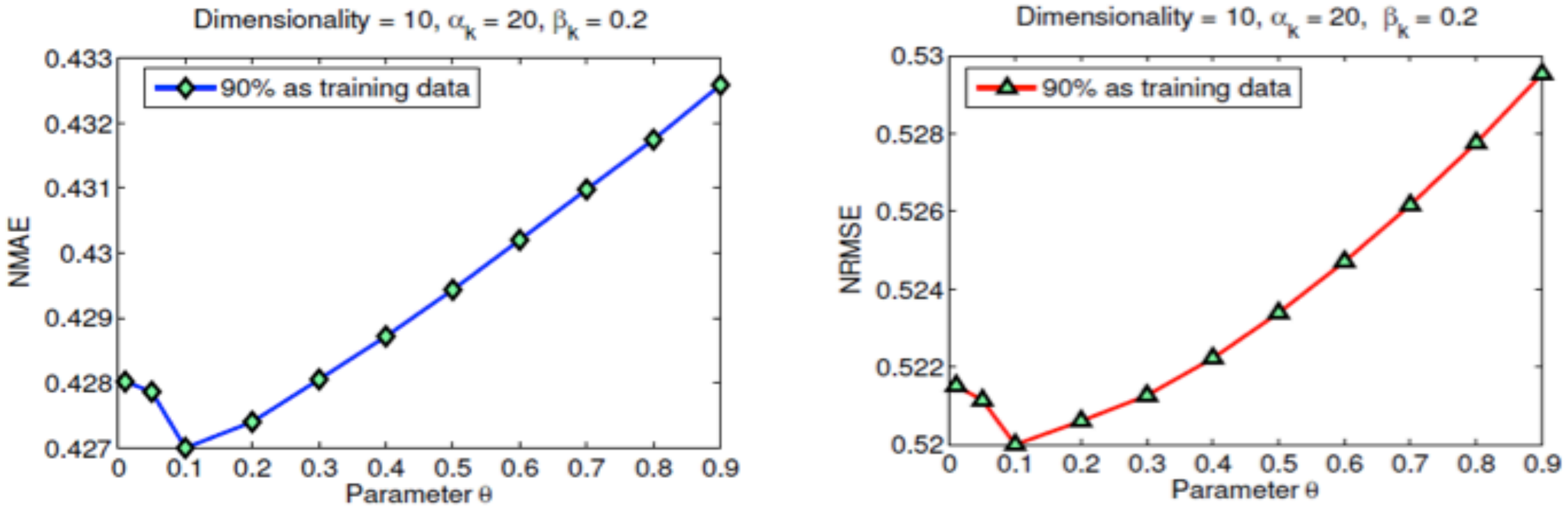
**Figure 6: Impact of Parameter $\alpha_k$ in PFM**



(a) NMAE (b) NRMSE (c) Gamma Distributions

**Figure 7: Impact of Parameter $\beta_k$ in PFM**

# Impact of Parameters



(a) NMAE

(b) NRMSE

**Figure 8: Impact of Parameter $\theta$ in CPFM**

# Concluding Remarks

- Social recommendation extends traditional models and techniques by using social graphs, ensembles, distrust relationships, clicks, etc.
- Fusing of social behavior information, e.g., social relationships, personal preferences, media consumption patters, temporal dynamics, location information, etc. provides better models for social recommendations

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