

# Recent Developments in Social and Location Recommendations

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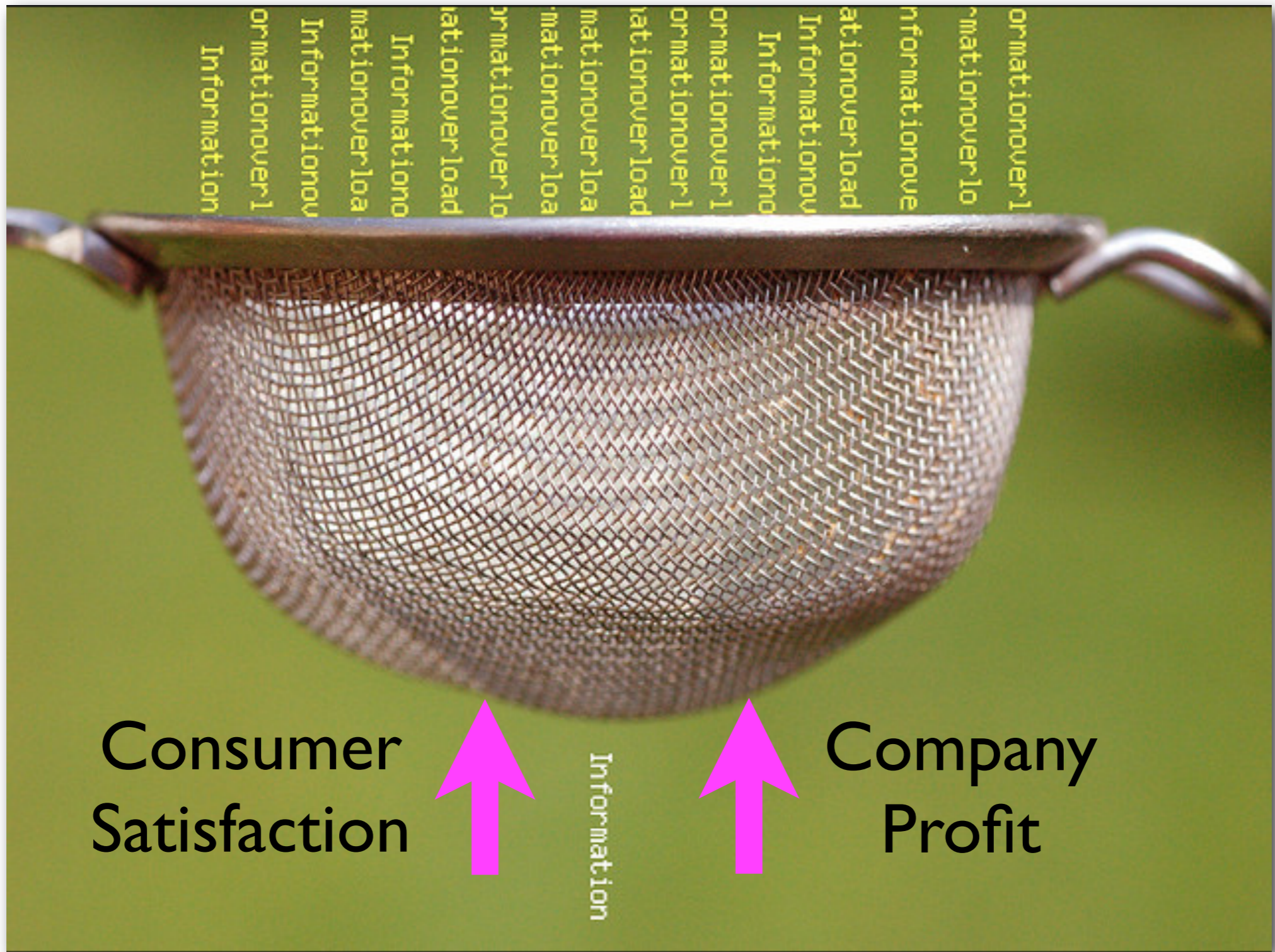
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CCF ADL 39 on Social Networks and Mining, August 3-5, 2013, Beijing, China





# Real Life Examples

The screenshot shows the Amazon.com interface for a book. At the top, the Amazon logo is on the left, and navigation links like 'Hello, Sign in', 'Today's Deals', and 'Gifts & Wish Lists' are in the center. On the right, there's a 'FREE 2-Day Shipping' offer and links for 'Your Digital Items', 'Your Account', and 'Help'. Below this is a search bar with 'Books' entered, and buttons for 'Shop All Departments', 'Cart', and 'Wish List'. A secondary navigation bar includes 'Books', 'Advanced Search', 'Browse Subjects', 'New Releases', 'Bestsellers', 'The New York Times® Bestsellers', 'Libros en español', 'Bargain Books', and 'Textbooks'. The main product area features a book cover on the left with a 'Click to LOOK INSIDE!' callout. The title is 'Weaving Services and People on the World Wide Web [Hardcover]' by Irwin King and Ricardo Baeza-Yates. The price is \$79.11, down from \$99.00, with a 'FREE with Super Saver Shipping' offer. A 'More Buying Choices' section shows 31 used and new copies for \$14.62. A 'Customers Who Bought This Item Also Bought' section is highlighted with a red oval and shows a book titled 'Social Web Analytics'. At the bottom, there are social sharing icons and a 'Share' button.

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# Real Life Examples

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http://www.amazon.com/Social-Computing-Behavioral-Modeling-Prediction/

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Predictably Irrational: Hidden Forces That... by Ariely

★★★★☆ (18) \$16.34

Generative Social Science: Studies in Agent-Bas... by Joshua M. Epstein

★★★★☆ (5) \$42.00

**Editorial Reviews**

**Product Description**

Social computing concerns... reproduces the social behavior, and allows for experimenting with and deep understanding of behavior, patterns, and potential

Five scales rating

★ I hate it

★★ I don't like it




★★★ It's ok

★★★★ I like it

★★★★★ I love it



# Real Life Examples

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Here's a daily sample of items recommended for you. Click here to [see all recommendations](#).

Page 1 of 25



[Invincible](#)  ~ Michael Jackson  
★★★★☆ (880) \$7.99



[In Search of Sunrise, Vol. 7: Asia](#)  ~ DJ Tiesto  
★★★★☆ (53) \$15.99



[Fallen](#)  ~ Evanescence  
★★★★☆ (2,447) \$8.99



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★★★★☆ (55) \$8.49





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Yahoo! Users: **B-** 4794 ratings

The Critics: **B** 14 reviews

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### Pride and Glory (R)

[Showtimes & Tickets](#) | [Add to My Lists](#)

Yahoo! Users: **A-** 59 ratings

The Critics: **C+** 6 reviews

Don't Recommend Again  Seen It? Rate It!



### Fight Club (R)

[Showtimes & Tickets](#) | [Add to My Lists](#)

Yahoo! Users: **B+** 52392 ratings

The Critics: **B** 12 reviews

Don't Recommend Again  Seen It? Rate It!



### Lakeview Terrace (PG-13)

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Yahoo! Users: **B** 3229 ratings

The Critics: **C** 12 reviews

Don't Recommend Again  Seen It? Rate It!



### 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](#)



# Real Life Examples



iTunes 8



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# On The Menu

- Introduction
- Social Recommendation Models
  - Social graph
  - Social ensemble
  - Social distrust
  - Website recommendation
- Multi-centered Gaussian Location Recommendation Model
- Conclusion



# Basic Approaches

- Content-based Filtering
  - Recommend items based on **key-words**
  - More appropriate for **information retrieval**
- Collaborative Filtering (CF)
  - Look at users with **similar rating styles**
  - Look at **similar items** for each item

**Underling assumption: personal tastes are correlated--**  
Active users will prefer those items which other  
similar users prefer!





# Framework

		Items												
		$i_1$	$i_2$			$i_j$							$i_m$	
Users	$u_1$													
	$u_2$	1	3		4		2		5			3	4	
	$u_i$		3		4		$r_{ij}$	3	4		3	4		4
	$u_n$	1			3	5	2		4	1			3	

- The tasks

- Find the unknown rating!
- Which item should be recommended?



# Social Recommender Systems

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



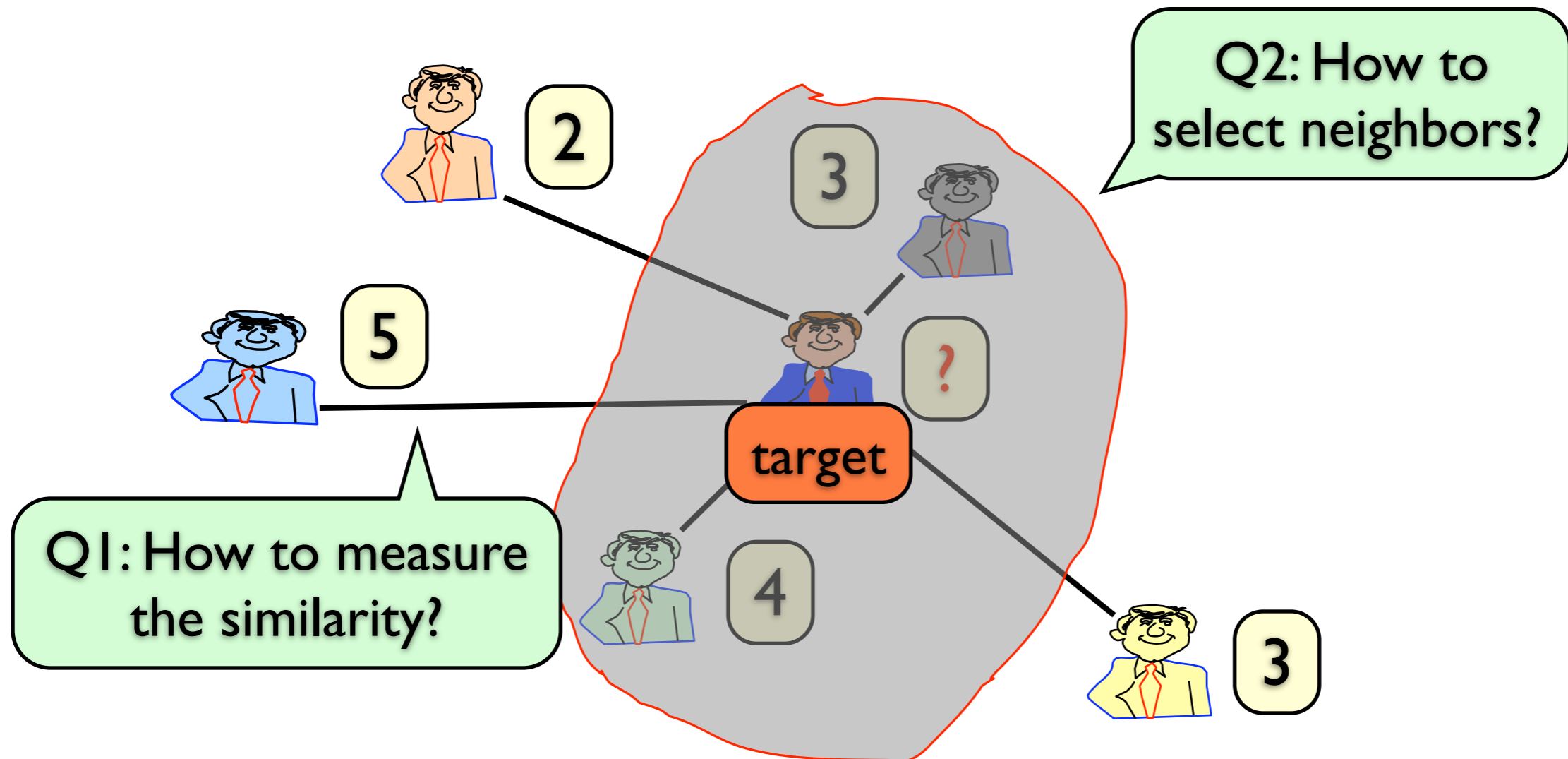
# Collaborative Filtering

- Memory-based (Neighborhood-based)
  - User-based
  - Item-based
- Model-based
  - Clustering Methods
  - Bayesian Methods
  - Matrix Factorization
  - etc.





# User-User Similarity



# User-based Collaborative Filtering

Items

Users

u <sub>1</sub>													
u <sub>2</sub>	1	3		4		2		5			3	4	
u <sub>3</sub>													
u <sub>4</sub>		3		4			3	4		3	4		4
u <sub>5</sub>													
u <sub>6</sub>	1			3	5	2		4	1			3	





# User-based Collaborative Filtering

Items

Users

u <sub>1</sub>												
u <sub>2</sub>	1	3	4		2		5			3	4	
u <sub>3</sub>												
u <sub>4</sub>		3	4			3	4		3	4		4
u <sub>5</sub>												
u <sub>6</sub>	1		3	5	2		4	1			3	



# User-based Collaborative Filtering

Items

Users

u <sub>1</sub>													
u <sub>2</sub>	1	3	4	2	5			3	4				
u <sub>3</sub>													
u <sub>4</sub>		3	4		3	4		3	4			4	
u <sub>5</sub>													
u <sub>6</sub>	1		3	5	2	4	1				3		





# User-based Collaborative Filtering

Items

Users

u <sub>1</sub>													
u <sub>2</sub>	1	3		4		2		5			3	4	
u <sub>3</sub>													
u <sub>4</sub>		3		4			3	4		3	4		4
u <sub>5</sub>													
u <sub>6</sub>	1			3	5	2		4	1			3	



# User-based Collaborative Filtering

Items

Users

u <sub>1</sub>													
u <sub>2</sub>	1	3	4		2		5			3	4		
u <sub>3</sub>													
u <sub>4</sub>		3	4			3	4		3	4		4	
u <sub>5</sub>													
u <sub>6</sub>	1		3	5	2		4	1			3		





# User-based Collaborative Filtering

- Predict the ratings of active users based on the ratings of similar users found in the user-item matrix
- Pearson correlation coefficient

$$w(a, i) = \frac{\sum_j (r_{aj} - \bar{r}_a)(r_{ij} - \bar{r}_i)}{\sqrt{\sum_j (r_{aj} - \bar{r}_a)^2 \sum_j (r_{ij} - \bar{r}_i)^2}} \quad j \in I(a) \cap I(i)$$

- Cosine measure

$$c(a, i) = \frac{r_a \cdot r_i}{\|r_a\|_2 * \|r_i\|_2}$$

$u_i$	1	3	4	2	5		3	4				
$u_a$	3	4		3	4	3	4	4				
	1		3	5	2	4	1		3			



# Nearest Neighbor Approaches

[Sarwar, 00a]

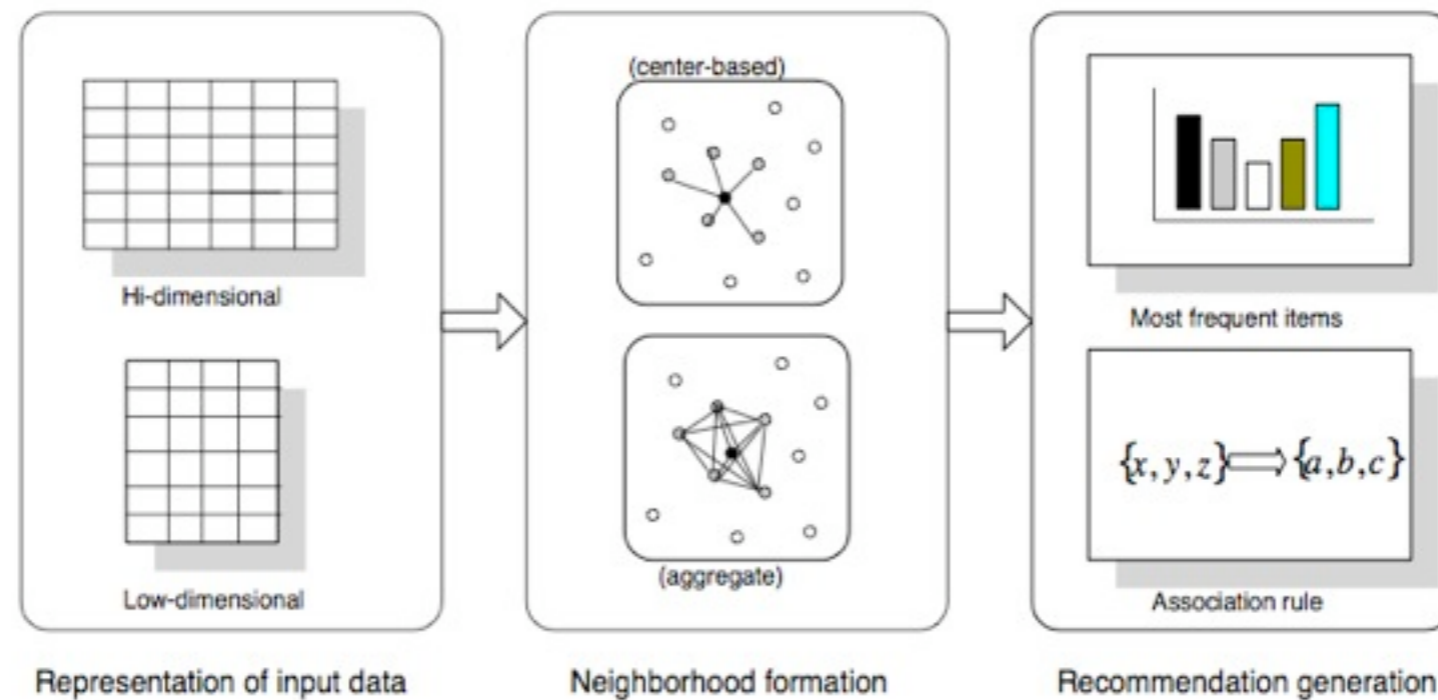


Figure 1: Three main parts of a Recommender System.

- Identify highly similar users to the active one
  - All with a measure greater than a threshold
  - Best K ones

- Prediction 
$$r_{aj} = \bar{r}_a + \frac{\sum_i w(a, i)(r_{ij} - \bar{r}_i)}{\sum_i w(a, i)}$$

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# Collaborative Filtering

- **Memory-based Method (Simple)**
  - User-based Method [Xue et al., SIGIR '05]
  - Item-based [Deshpande et al., TOIS '04]
- **Model-based (Robust)**
  - Clustering Methods [Hkors et al, CIMCA '99]
  - Bayesian Methods [Chien et al., IWAIIS '99]
  - Aspect Method [Hofmann, SIFIR '03]
  - Matrix Factorization [Sarwar et al., WWW '01]



# Collaborative Filtering

- Memory-based (Neighborhood-based)
  - User-based
  - Item-based
- Model-based
  - Clustering Methods
  - Bayesian Methods
  - Matrix Factorization
  - etc.





# Item-Item Similarity

- Search for similarities among items
- Item-Item similarity is more stable than user-user similarity



# Correlation-based Methods

[Sarwar, 2001]

- Same as in user-user similarity but on item vectors
- Pearson correlation coefficient
- Look for users who rated both items

$$s_{ij} = \frac{\sum_u (r_{uj} - \bar{r}_j)(r_{ui} - \bar{r}_i)}{\sqrt{\sum_u (r_{uj} - \bar{r}_j)^2 \sum_u (r_{ui} - \bar{r}_i)^2}}$$

- $u$ : users rated both items

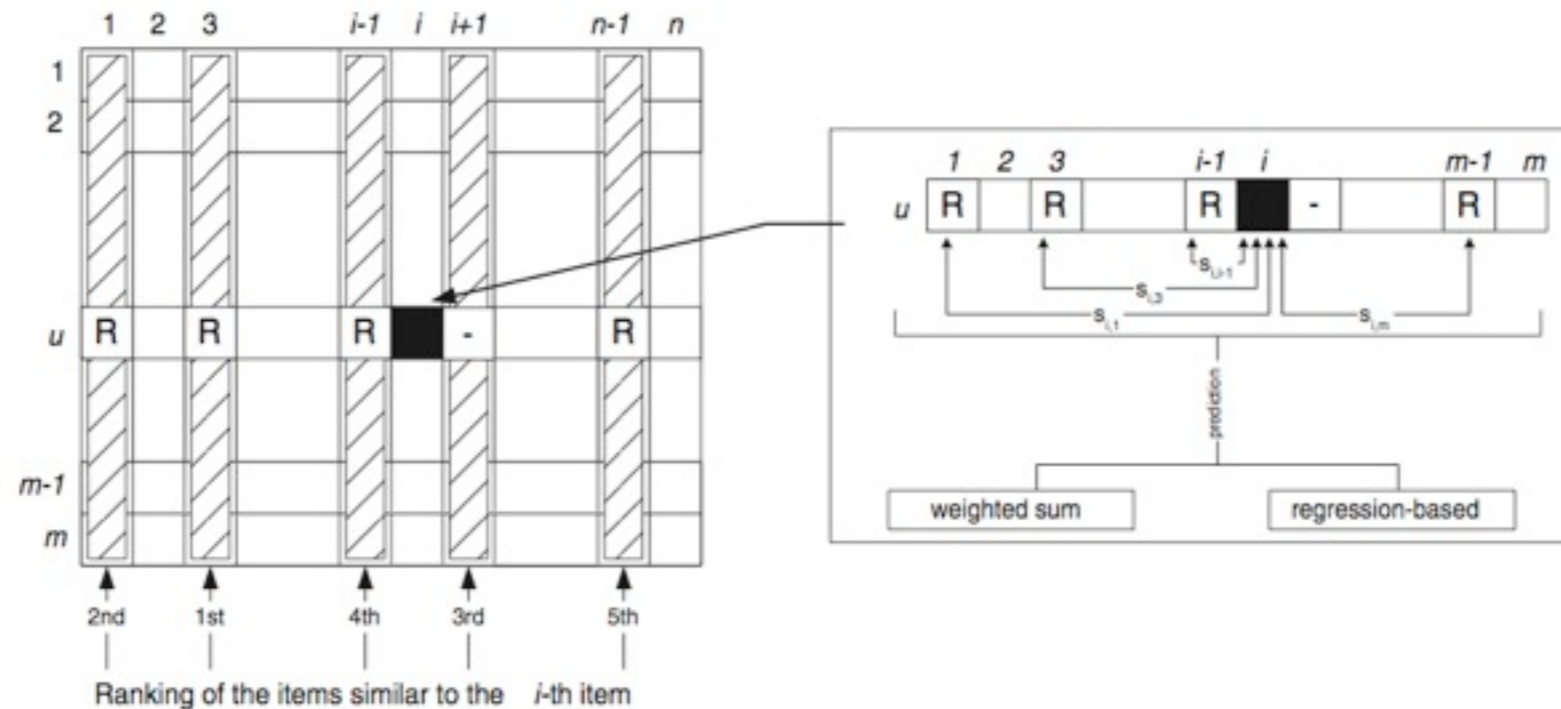
	$i_1$	$i_2$			$i_i$	$i_j$				$i_m$
$u_1$										
$u_2$	1	3		4	2	5			3	4
$u_i$		3		4		3	4		3	4
$u_n$	1			3	5	2	4	1		3



# Correlation-based Method

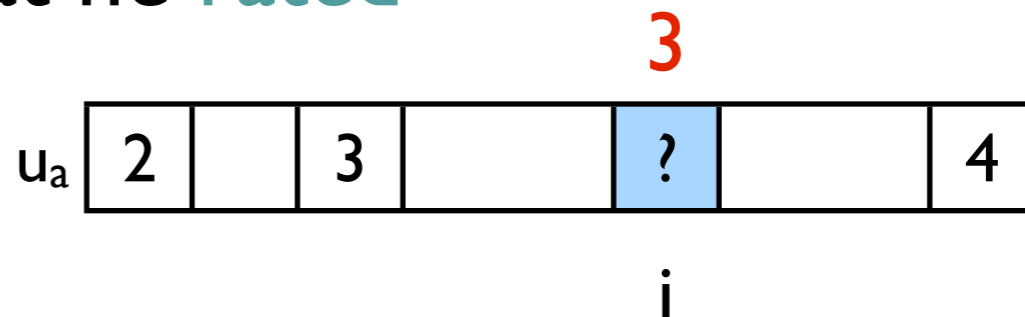
[Sarwar, 2001]

- Calculate item similarity, then determine its **k-most similar** items



- Predict rating for a given user-item pair as a **weighted sum** over **similar items** that he **rated**

$$r_{ai} = \frac{\sum_j s_{ij} r_{aj}}{\sum_j s_{ij}}$$



# Traditional Methods

- Memory-based Methods (Neighborhood-based Method)
  - Pearson Correlation Coefficient
  - User-based, Item-based
  - Etc.
- Model-based Method
  - Matrix Factorizations
  - Etc.

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





# User-based Method

Items

Users

$u_1$												
$u_2$	1	3	4	2	5			3	4			
$u_3$												
$u_4$		3	4		3	4		3	4		4	
$u_5$												
$u_6$	1		3	5	2		4	1			3	



# Collaborative Filtering

- Memory-based (Neighborhood-based)
  - User-based
  - Item-based
- Model-based
  - Clustering Methods
  - Bayesian Methods
  - **Matrix Factorization**
  - etc...



# Matrix Factorization

	$i_1$	$i_2$	$i_3$	$i_4$	$i_5$	$i_6$	$i_7$	$i_8$
$u_1$	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

	$i_1$	$i_2$	$i_3$	$i_4$	$i_5$	$i_6$	$i_7$	$i_8$
$u_1$	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

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

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



# Matrix Factorization

- Matrix Factorization in Collaborative Filtering
  - To fit the product of two (low rank) matrices to the observed rating matrix
  - To find two latent user and item feature matrices
  - To use the fitted matrix to predict the unobserved ratings

$$\begin{pmatrix} \mathbf{u}_{11} & \cdots & \mathbf{u}_{1k} \\ \vdots & \ddots & \vdots \\ \mathbf{u}_{m1} & \cdots & \mathbf{u}_{mk} \end{pmatrix} \begin{pmatrix} \mathbf{v}_{11} & \cdots & \mathbf{v}_{1n} \\ \vdots & \ddots & \vdots \\ \mathbf{v}_{k1} & \cdots & \mathbf{v}_{kn} \end{pmatrix}$$

Diagram illustrating matrix factorization. The first matrix (User-specific latent feature matrix) is shown with a red box around the first row and a blue arrow pointing to the label "User-specific latent feature vector". The second matrix (Item-specific latent feature matrix) is shown with a blue box around the first column and a red arrow pointing to the label "Item-specific latent feature column vector".





# Matrix Factorization

- Optimization Problem
- Given a  $m \times n$  rating matrix  $R$ , to find two matrices  $U \in \mathbb{R}^{l \times m}$  and  $V \in \mathbb{R}^{l \times n}$ ,

$$R \approx U^T V,$$

where  $l < \min(m, n)$ , is the number of factors



# Matrix Factorization

- Models
  - SVD-like Algorithm
  - Regularized Matrix Factorization (RMF)
  - Probabilistic Matrix Factorization (PMF)
  - Non-negative Matrix Factorization (NMF)
  - ...



# SVD-like Algorithm

- Minimizing

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

- For collaborative filtering

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

where  $I_{ij}$  is the indicator function that is equal to 1 if user  $u_i$  rated item  $v_j$  and equal to 0 otherwise.



# Regularized Matrix Factorization

- Minimize the loss based on the observed ratings with regularization terms to avoid over-fitting problem

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

Regularization terms

where  $\lambda_1, \lambda_2 > 0$ .

- The problem can be solved by simple gradient descent algorithm.





# Regularized Matrix Factorization

- Algorithm for RMF
  - Not convex & local optimal
  - Gradient-descent algorithm
  - Gradient computation with randomly initialized  $U$  and  $V$

$$\frac{\partial L}{\partial u_{il}} = \lambda u_{il} - \sum_{j|(i,j) \in S} (y_{ij} - \hat{y}_{ij}) v_{jl}$$

$$\frac{\partial L}{\partial v_{jl}} = \lambda v_{jl} - \sum_{i|(i,j) \in S} (y_{ij} - \hat{y}_{ij}) u_{il}$$

- Update  $U$  and  $V$  alternatively

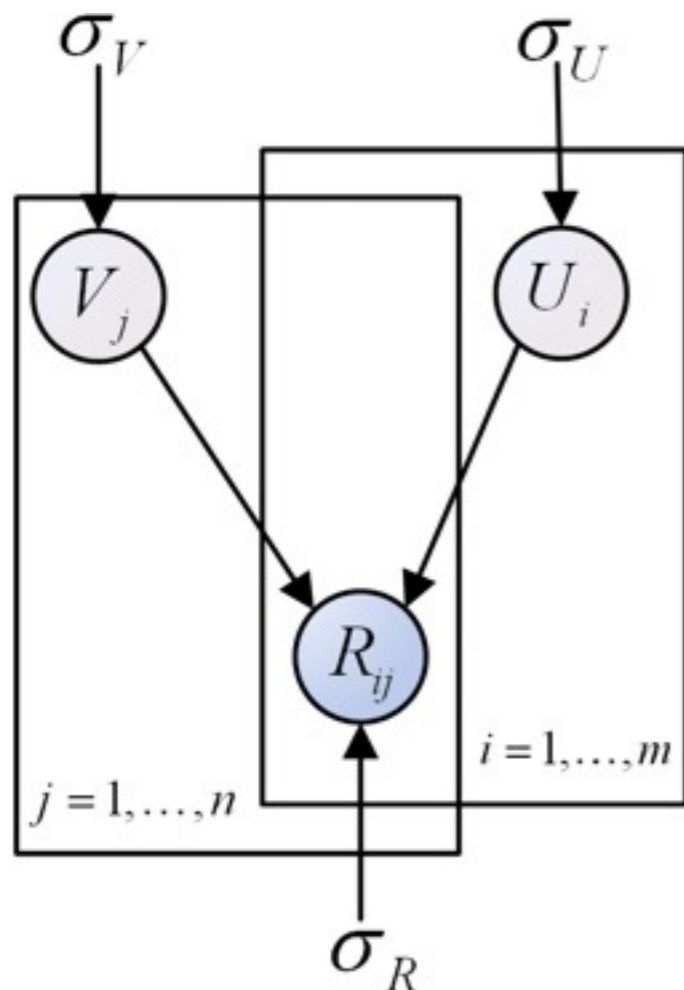
$$u_{il}^{(t+1)} = u_{il}^{(t)} - \tau \frac{\partial L}{\partial u_{il}^{(t)}}$$

$$v_{jl}^{(t+1)} = v_{jl}^{(t)} - \tau \frac{\partial L}{\partial v_{jl}^{(t)}}$$



# Probabilistic Matrix Factorization

- PMF
  - Define a conditional distribution over the observed ratings as:

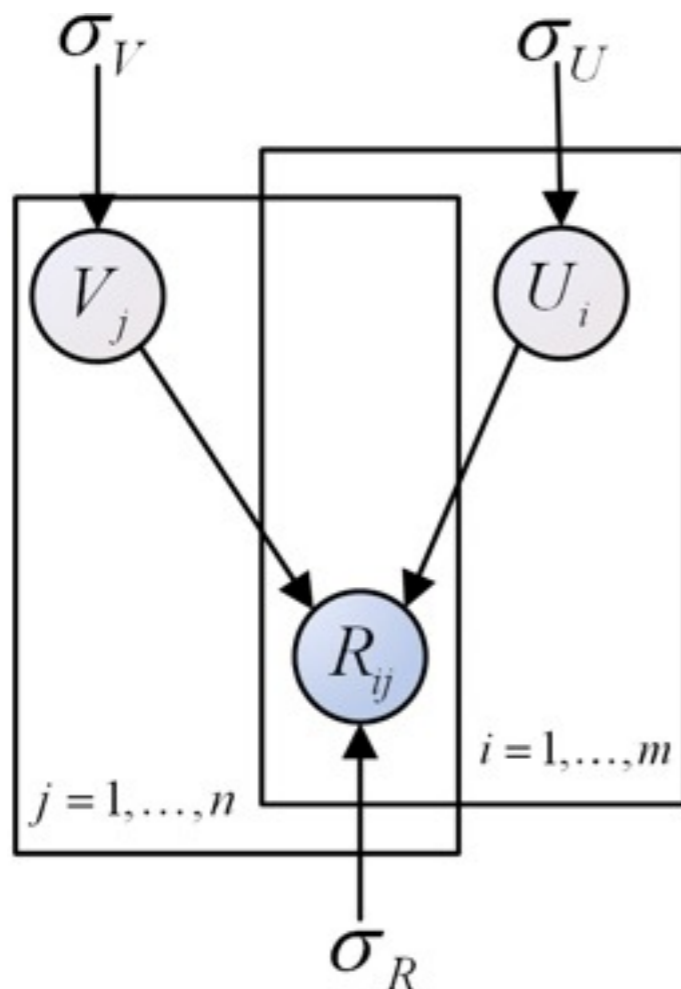


$$p(R|U, V, \sigma_R^2) = \prod_{i=1}^m \prod_{j=1}^n \left[ \mathcal{N} \left( R_{ij} | g(U_i^T V_j), \sigma_R^2 \right) \right]^{I_{ij}^R}$$



# Probabilistic Matrix Factorization

- PMF
  - Assume zero-mean spherical Gaussian priors on user and item feature:



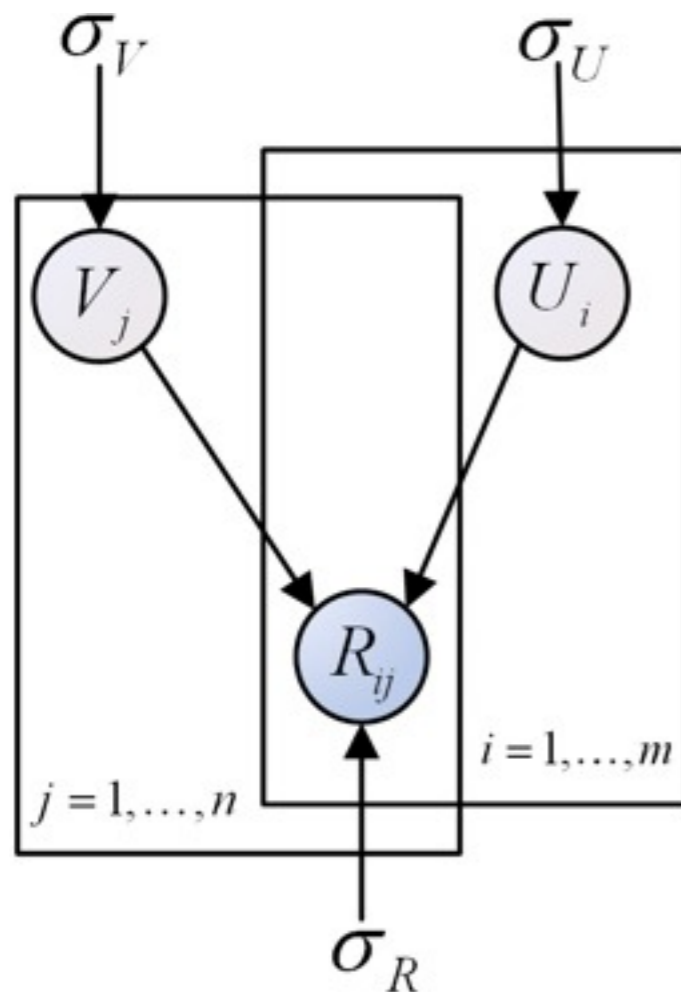
$$p(U|\sigma_U^2) = \prod_{i=1}^m \mathcal{N}(U_i | 0, \sigma_U^2 \mathbf{I})$$

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



# Probabilistic Matrix Factorization

- PMF
  - Bayesian inference



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



# RMF and PMF

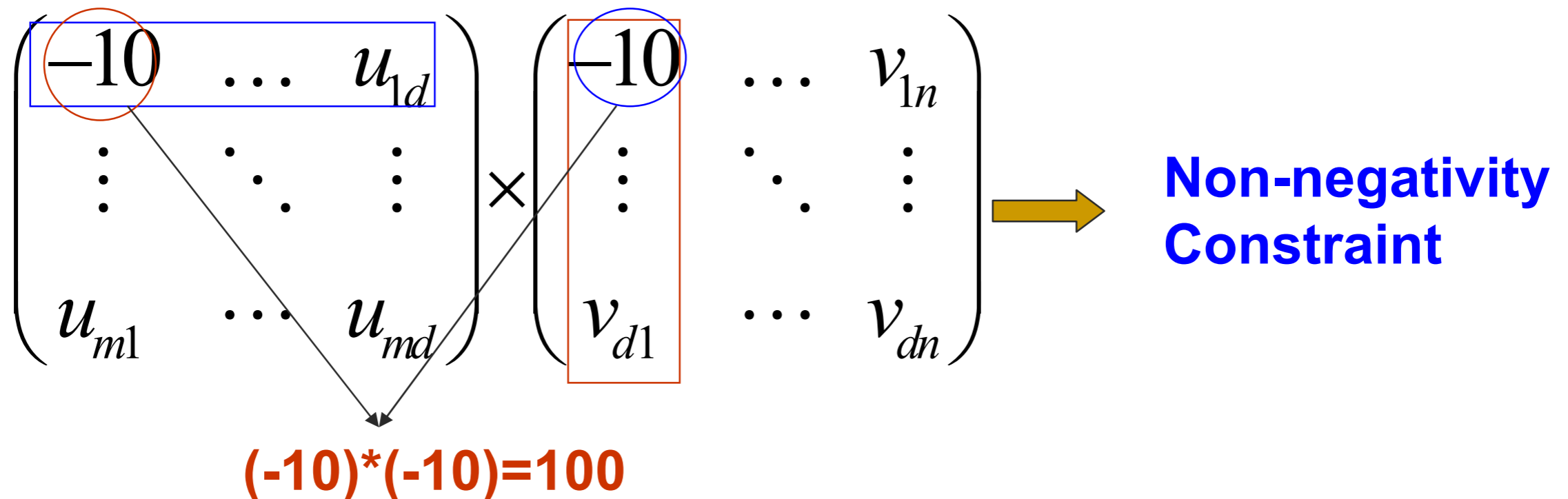
- PMF is the probabilistic interpretation of RMF
- PMF and RMF have the same optimization objective function





# Non-negative Matrix Factorization

- NMF
  - Non-negative constraints on all entries of matrices U and V



# Non-negative Matrix Factorization

- NMF
  - Given an observed matrix  $Y$ , to find two non-negative matrices  $U$  and  $V$
  - Two types of loss functions

- Squared error function

$$\sum_{ij} (R_{ij} - U_i^T V_j)^2$$

- Divergence

$$D(R||U^T V) = \sum_{ij} (R_{ij} \log \frac{R_{ij}}{U_i^T V_j} - R_{ij} + U_i^T V_j)$$

- Solving by multiplicative updating rules



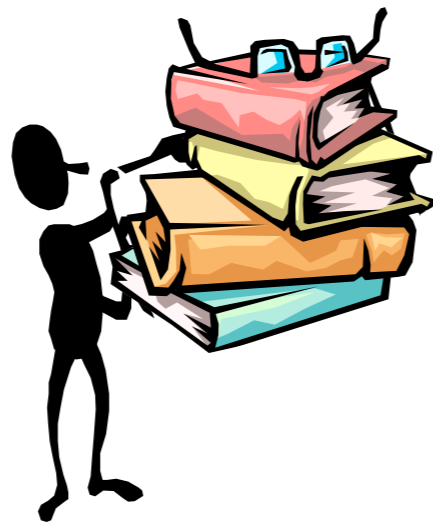
# Social Recommendation Using Probabilistic Matrix Factorization

[Ma et al., CIKM2008]



# Challenges

- Traditional recommender systems ignore the social connections between users



Which one should I choose?

Recommendations  
from friends



# Motivations

- “Yes, there is a correlation - from social networks to personal behavior on the web”

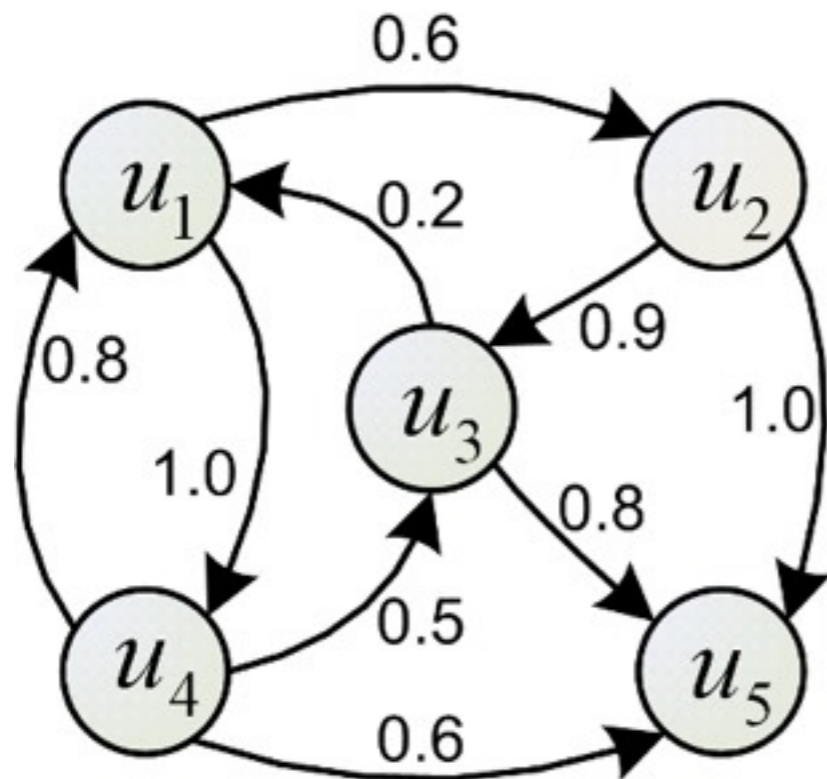
Parag Singla and Matthew Richardson ([WWW'08](#))

- 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

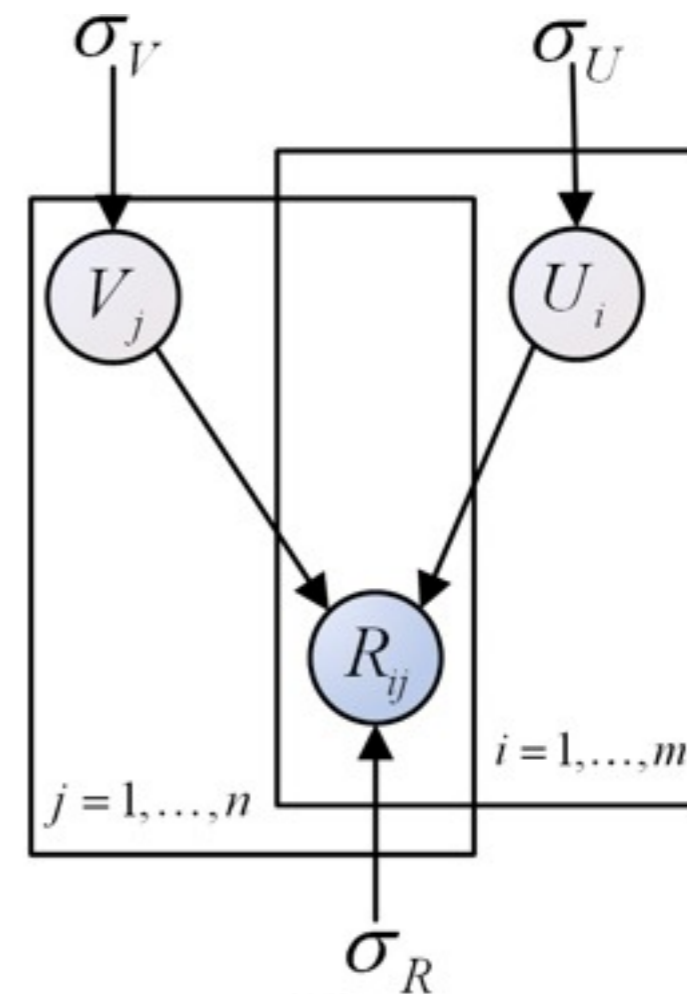
	$v_1$	$v_2$	$v_3$	$v_4$	$v_5$	$v_6$
$u_1$		5	2		3	
$u_2$	4			3		4
$u_3$			2			2
$u_4$	5			3		
$u_5$		5	5			3

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



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

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

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

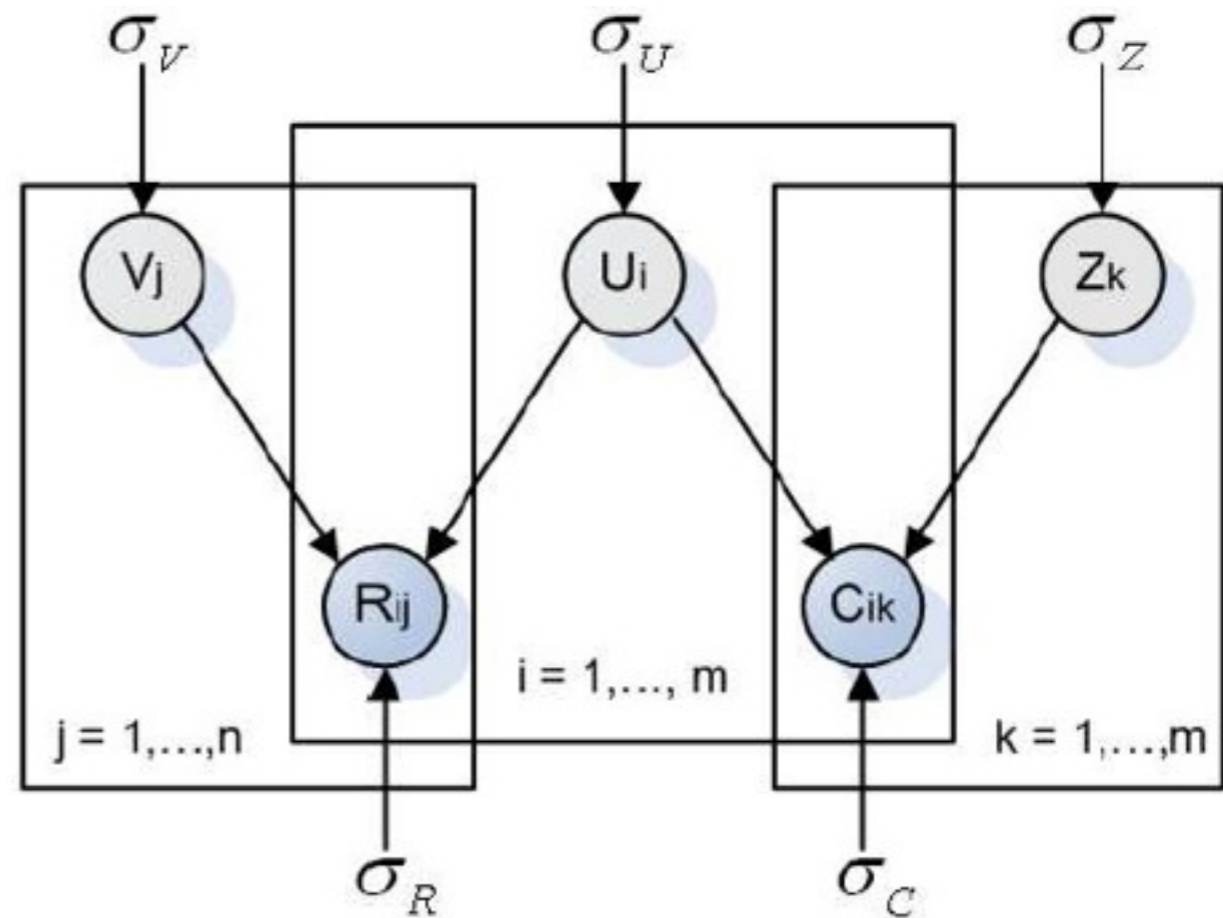
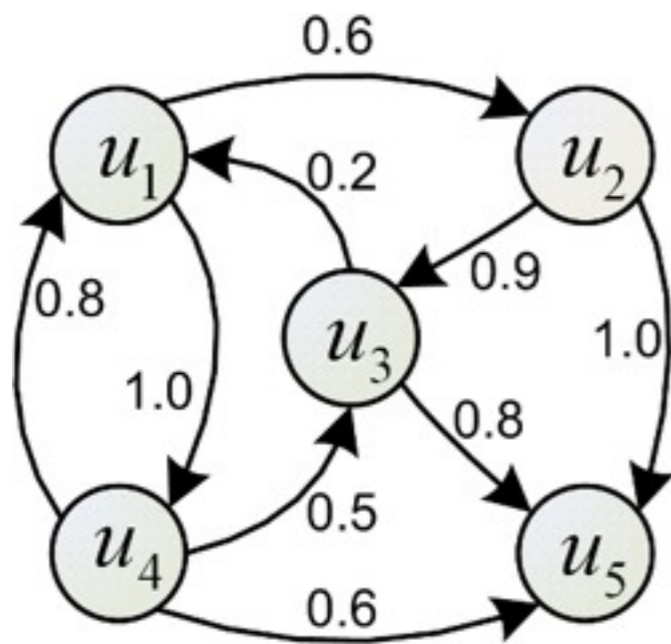
R. Salakhutdinov and A. Mnih (NIPS'08)

Recent Developments in Social and Location Recommendations, Irwin King  
CCF ADL 39 on Social Networks and Mining, August 3-5, 2013, Beijing, China



# SoRec

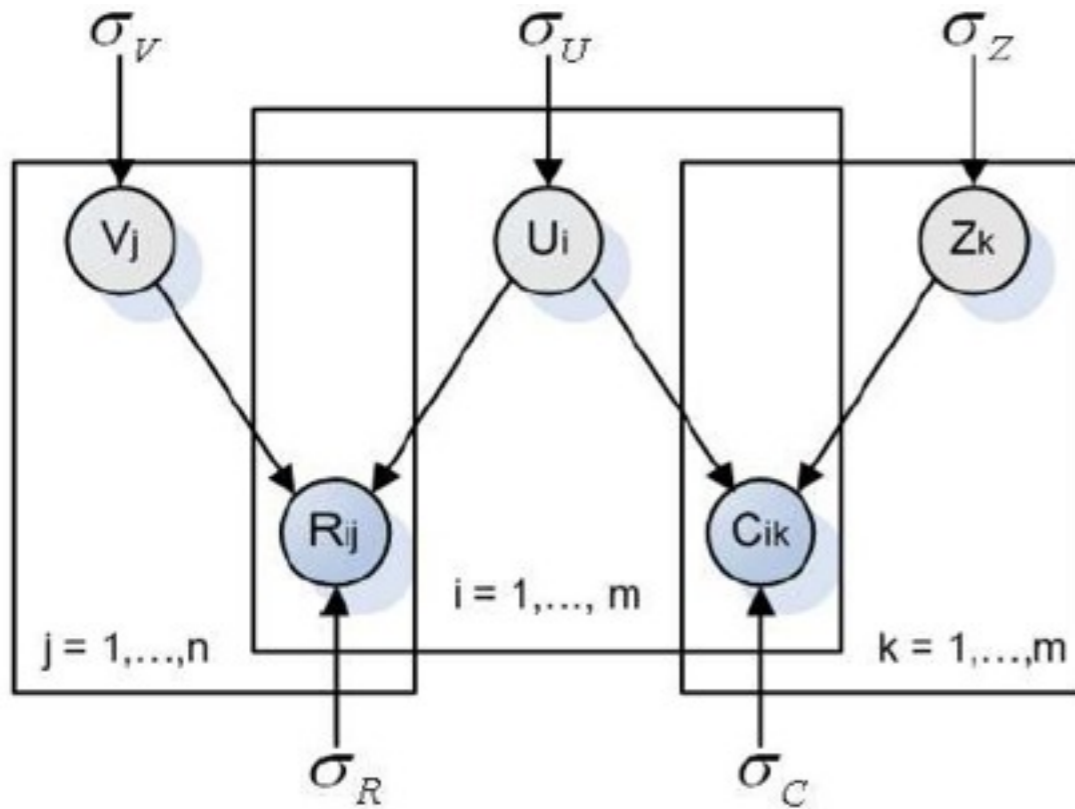
	$v_1$	$v_2$	$v_3$	$v_4$	$v_5$	$v_6$
$u_1$		5	2		3	
$u_2$	4			3		4
$u_3$			2			2
$u_4$	5			3		
$u_5$		5	5			3



SoRec



# SoRec



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

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

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

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

$$\mathcal{L}(R, C, U, V, Z) =$$

$$\frac{1}{2} \sum_{i=1}^m \sum_{j=1}^n I_{ij}^R (r_{ij} - g(U_i^T V_j))^2 + \frac{\lambda_C}{2} \sum_{i=1}^m \sum_{k=1}^m I_{ik}^C (c_{ik}^* - g(U_i^T Z_k))^2$$

$$+ \frac{\lambda_U}{2} \|U\|_F^2 + \frac{\lambda_V}{2} \|V\|_F^2 + \frac{\lambda_Z}{2} \|Z\|_F^2,$$



# SoRec

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

$$\frac{\partial \mathcal{L}}{\partial V_j} = \sum_{i=1}^m I_{ij}^R g'(U_i^T V_j) (g(U_i^T V_j) - r_{ij}) U_i + \lambda_V V_j,$$

$$\frac{\partial \mathcal{L}}{\partial Z_k} = \lambda_C \sum_{i=1}^m I_{ik}^C g'(U_i^T Z_k) (g(U_i^T Z_k) - c_{ik}^*) U_i + \lambda_Z Z_k,$$





# Complexity Analysis

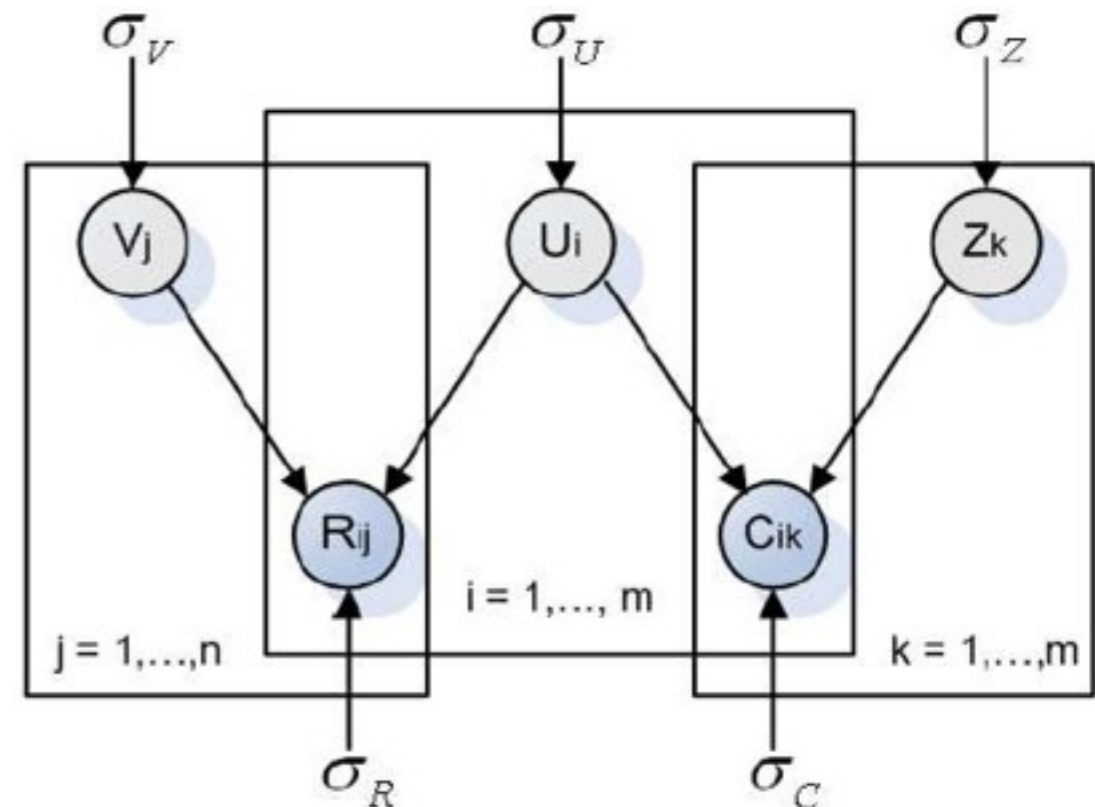
- For the Objective Function  $O(\rho_R l + \rho_C l)$
- For  $\frac{\partial \mathcal{L}}{\partial U}$  the complexity is  $O(\rho_R l + \rho_C l)$
- For  $\frac{\partial \mathcal{L}}{\partial V}$  the complexity is  $O(\rho_R l)$
- For  $\frac{\partial \mathcal{L}}{\partial Z}$  the complexity is 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





# Disadvantages of SoRec

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



SoRec



# Learning to Recommend with Social Trust Ensemble

[Ma et al., SIGIR2009]



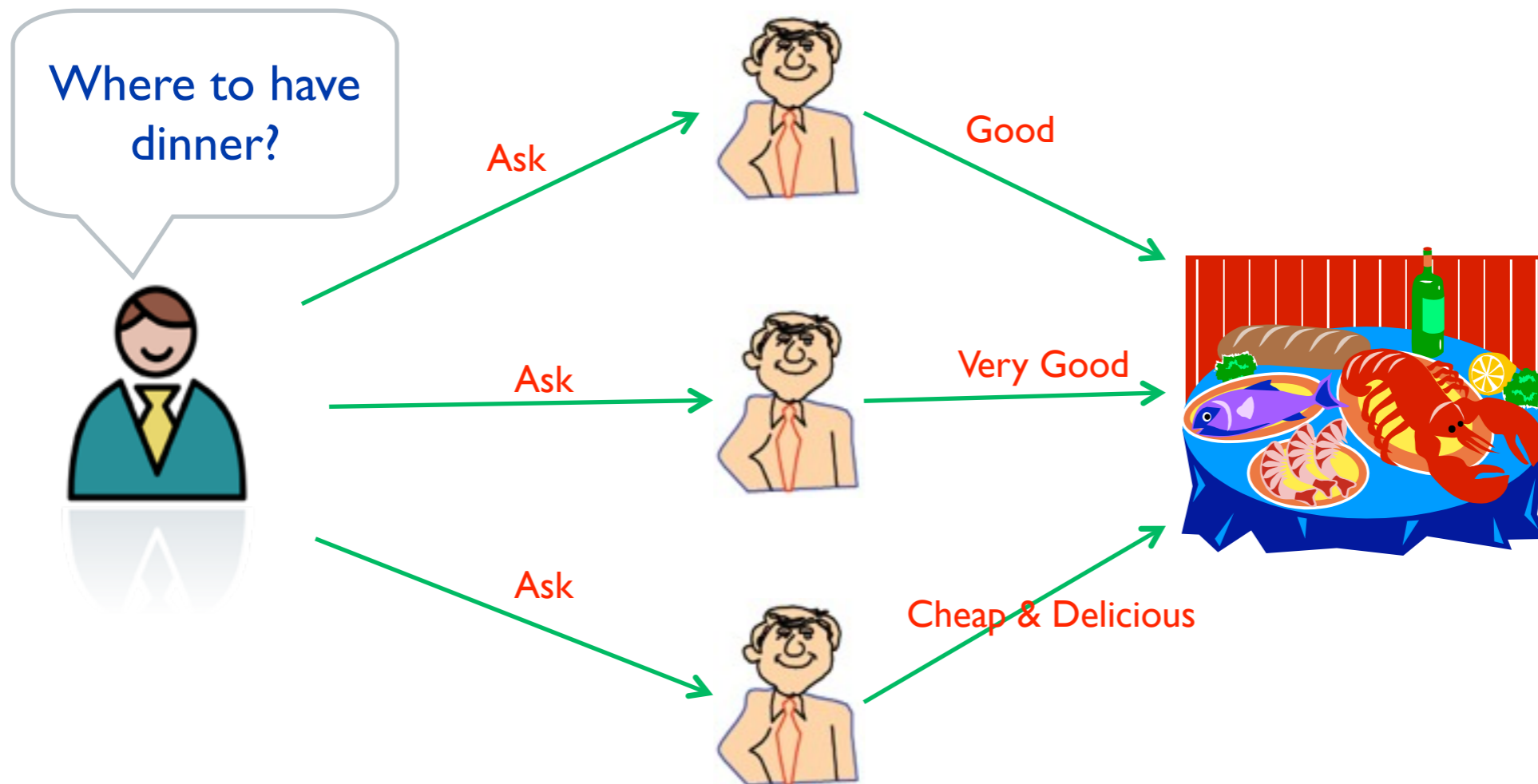
# 1<sup>st</sup> Motivation

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



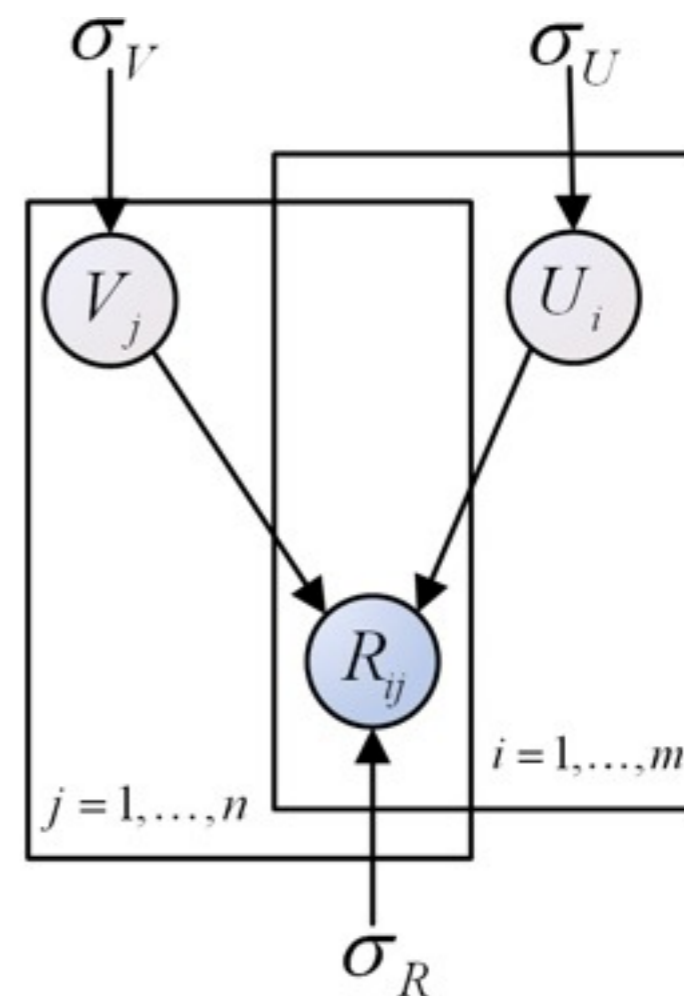
# 2<sup>nd</sup> Motivation

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



# 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



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

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

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

[R. Salakhutdinov, et al., NIPS2008]

Recent Developments in Social and Location Recommendations, Irwin King  
CCF ADL 39 on Social Networks and Mining, August 3-5, 2013, Beijing, China





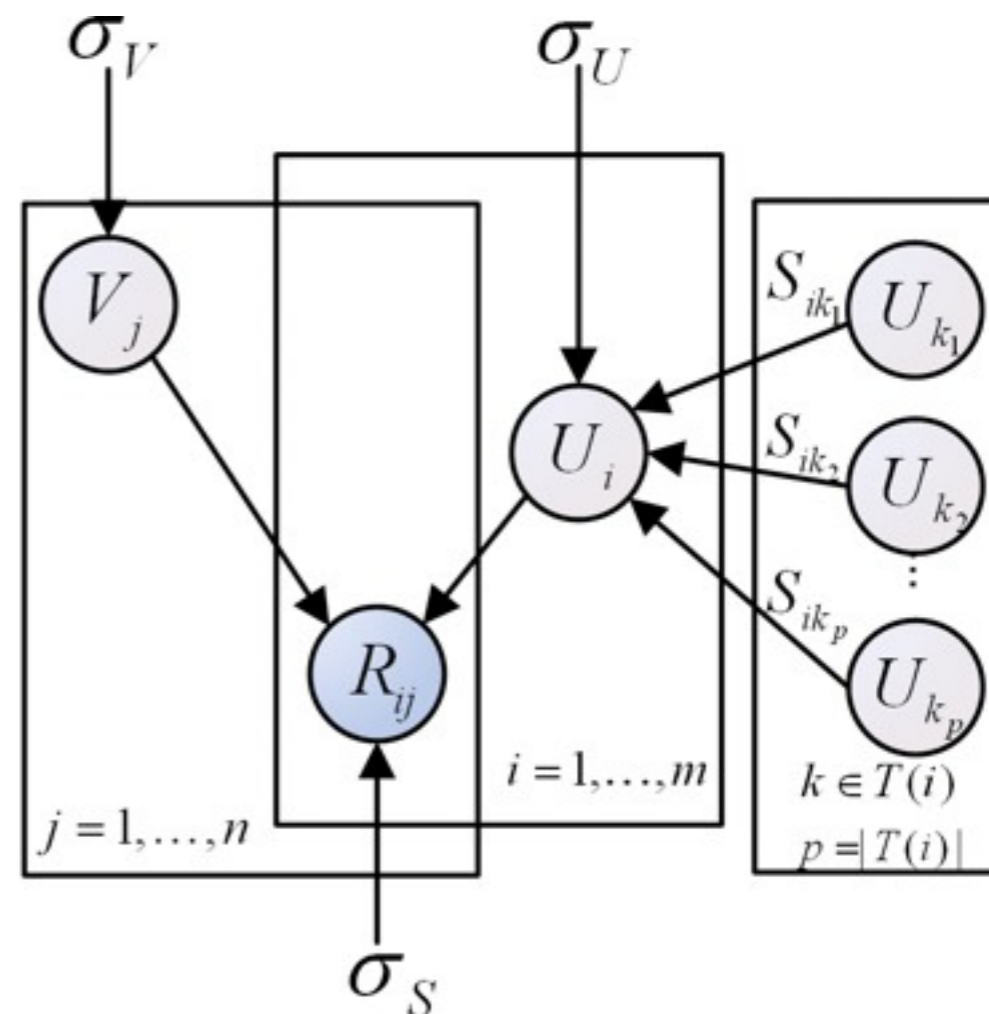
# Recommendations by Trusted Friends

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

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

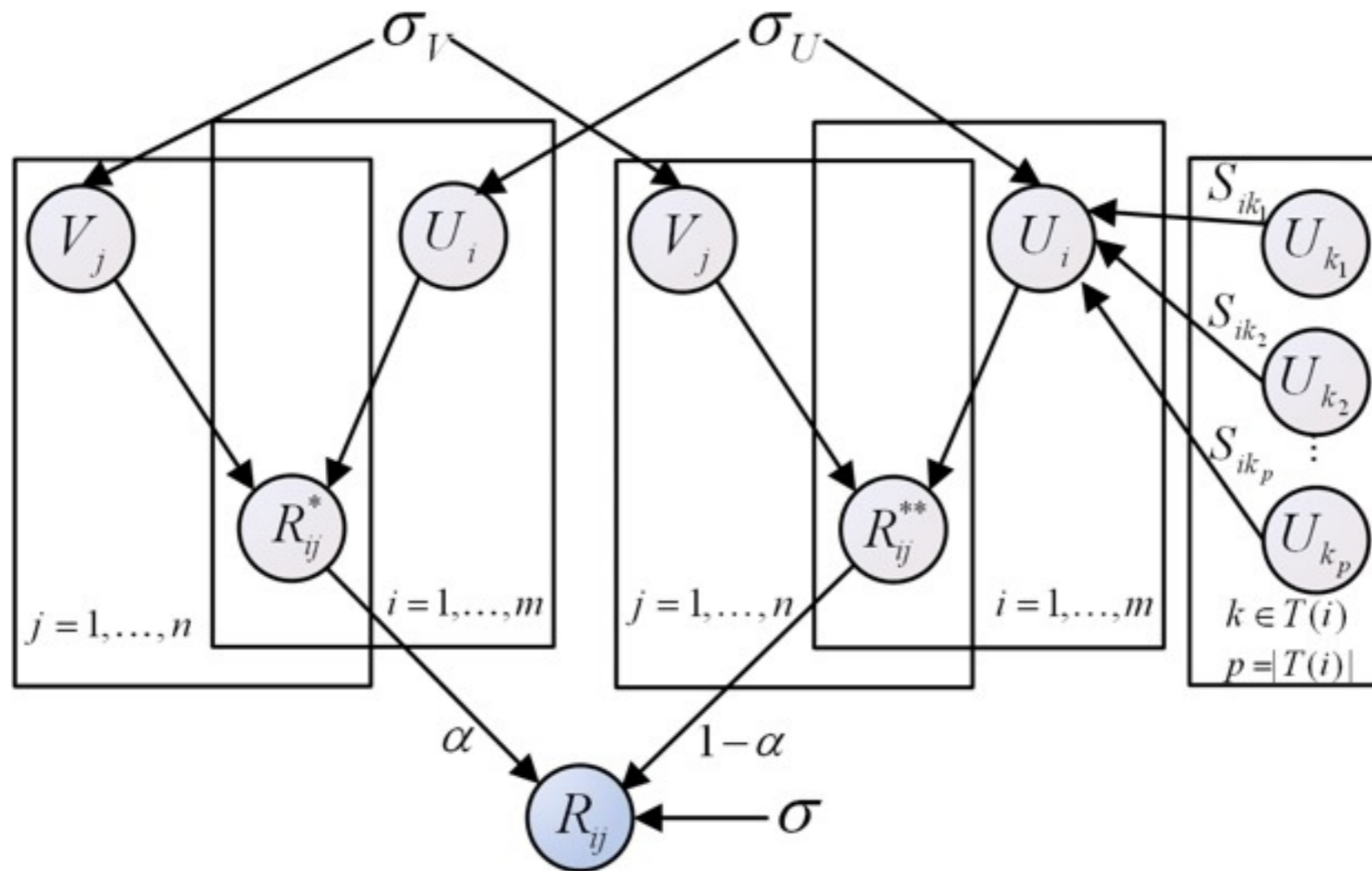
$$p(R|S, U, V, \sigma_R^2) =$$

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





# Recommendation with Social Trust Ensemble



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



# Recommendation with Social Trust Ensemble

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

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

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



# 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

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

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



# Comparisons

Table 3: Performance Comparisons (A Smaller MAE or RMSE Value Means a Better Performance)

Training Data	Metrics	Dimensionality = 5				Dimensionality = 10			
		Trust	PMF	SoRec	RSTE	Trust	PMF	SoRec	RSTE
90%	MAE	0.9054	0.8676	0.8484	<b>0.8377</b>	0.9039	0.8651	0.8426	<b>0.8367</b>
	RMSE	1.1959	1.1575	1.1418	<b>1.1109</b>	1.1917	1.1544	1.1365	<b>1.1094</b>
80%	MAE	0.9221	0.8951	0.8654	<b>0.8594</b>	0.9215	0.8886	0.8605	<b>0.8537</b>
	RMSE	1.2140	1.1826	1.1517	<b>1.1346</b>	1.2132	1.1760	1.1586	<b>1.1256</b>

**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)





# 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	<b>0.8377</b>
	RMSE	1.1688	1.2375	1.1649	1.1575	1.1959	1.1333	<b>1.1109</b>
80%	MAE	0.9285	0.9913	0.8975	0.8951	0.9221	0.8638	<b>0.8594</b>
	RMSE	1.1817	1.2584	1.1861	1.1826	1.2140	1.1530	<b>1.1346</b>

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	<b>0.8367</b>
	RMSE	1.1688	1.2375	1.1621	1.1544	1.1917	1.1293	<b>1.1094</b>
80%	MAE	0.9285	0.9913	0.8951	0.8886	0.9215	0.8580	<b>0.8537</b>
	RMSE	1.1817	1.2584	1.1832	1.1760	1.2132	1.1492	<b>1.1256</b>

**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)

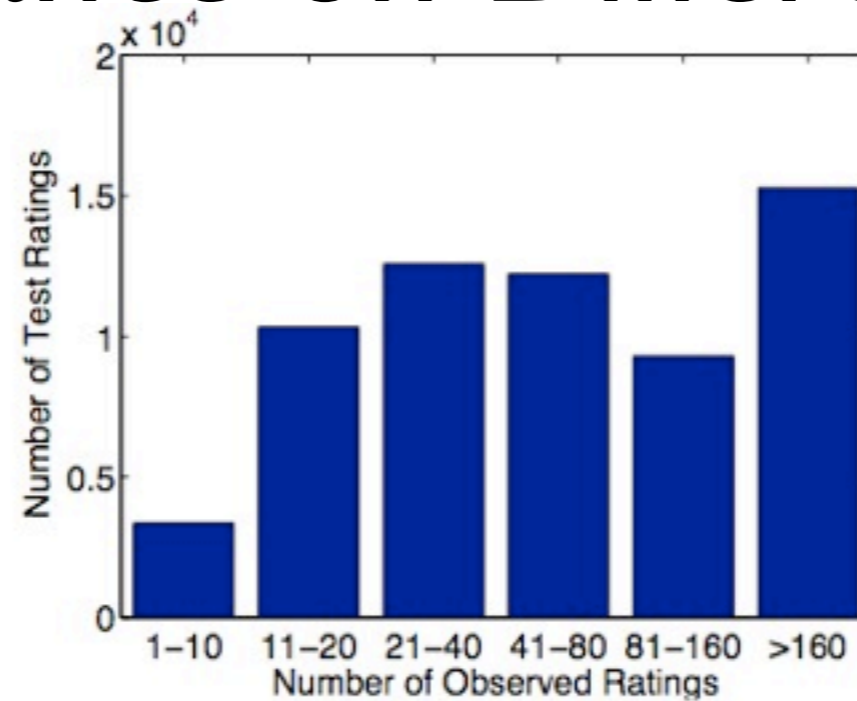


# Performance on Different Users

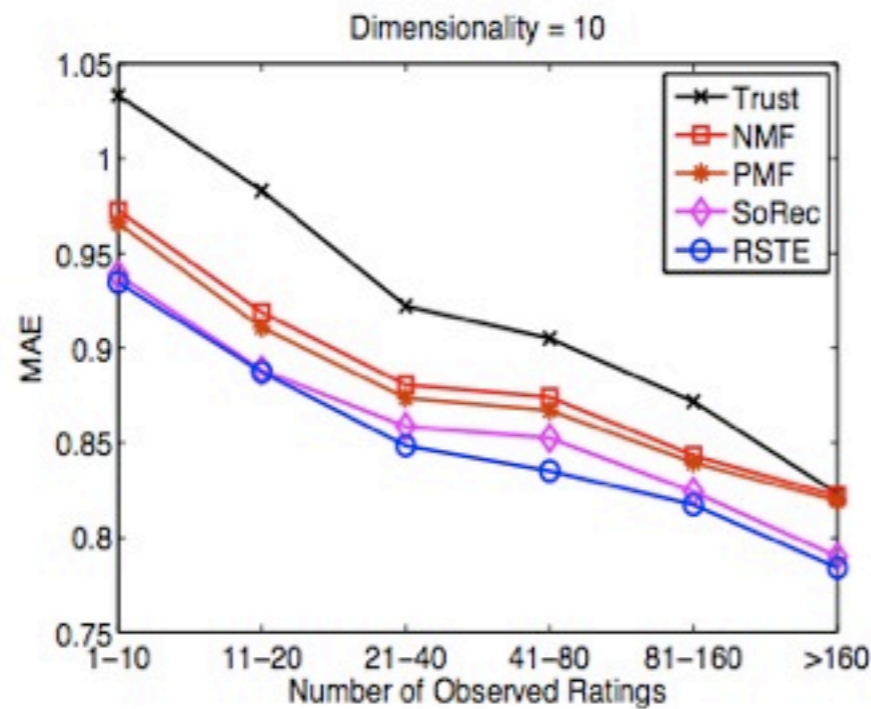
- Group all the users based on the number of observed ratings in the training data
- 6 classes: “1 – 10”, “11 – 20”, “21 – 40”, “41 – 80”, “81 – 160”, “> 160”,



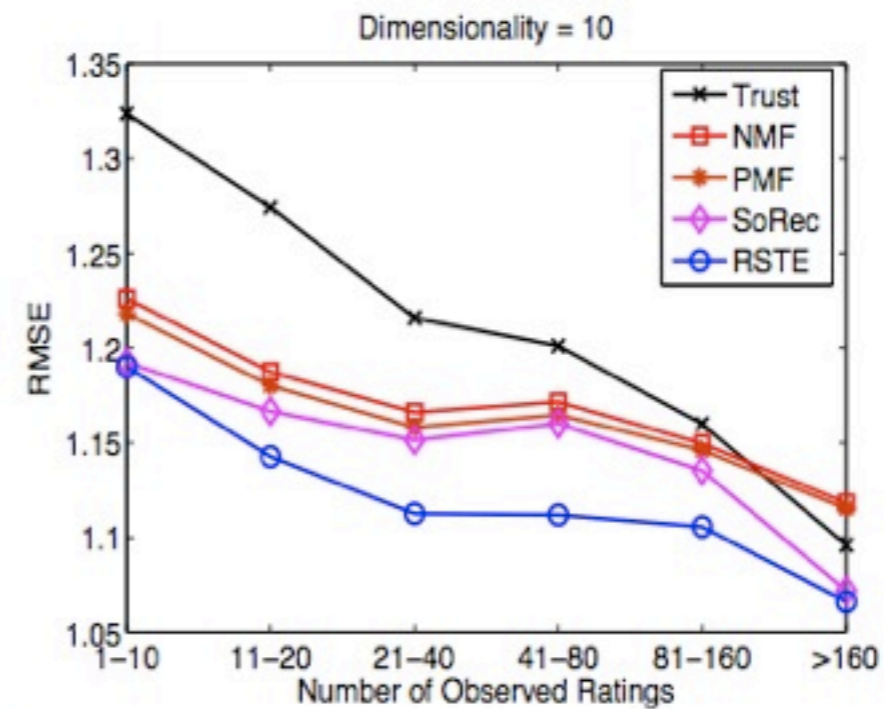
# Performance on Different Users



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



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



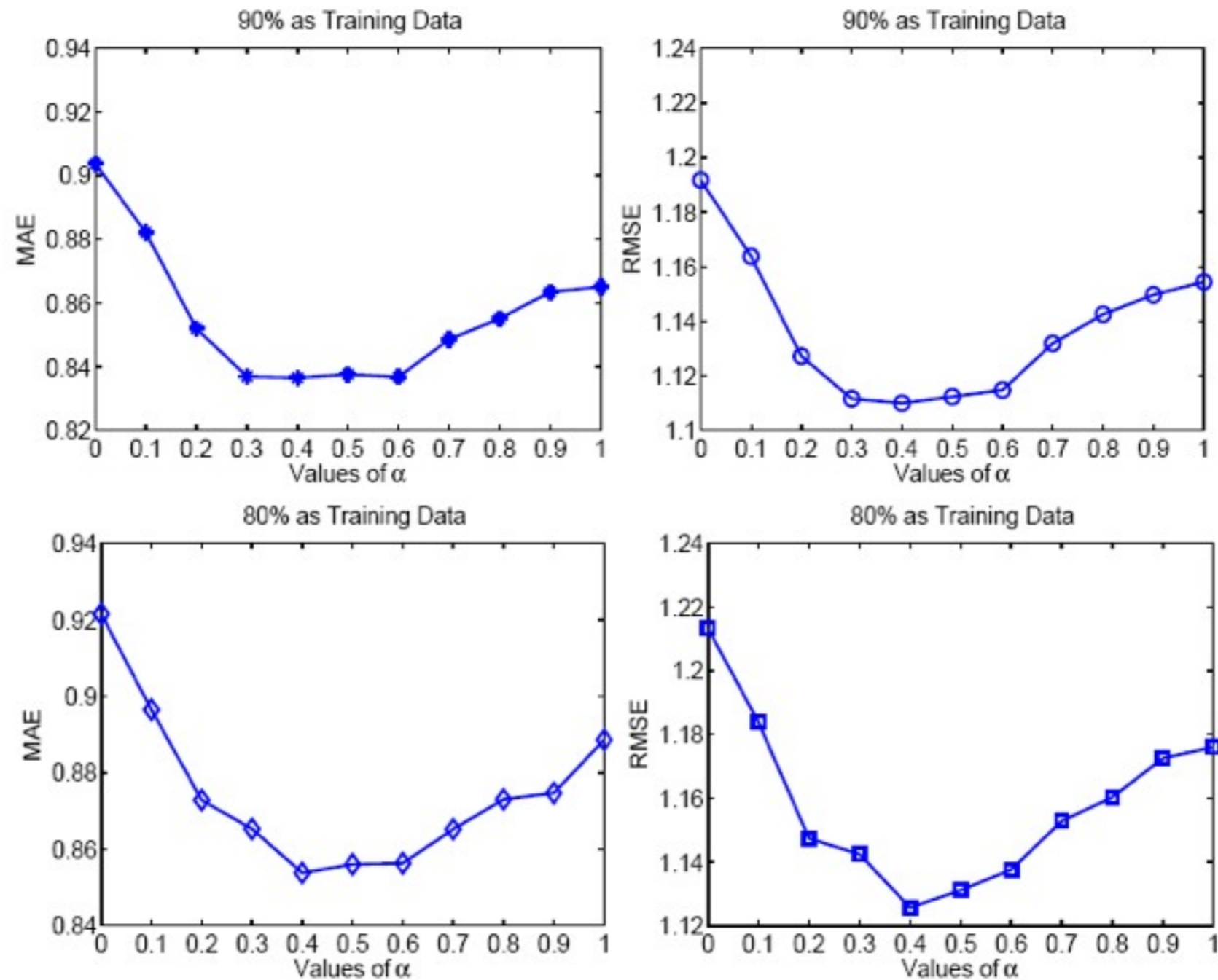
(c) RMSE Comparison on Different User Rating Scales (90% as Training Data)

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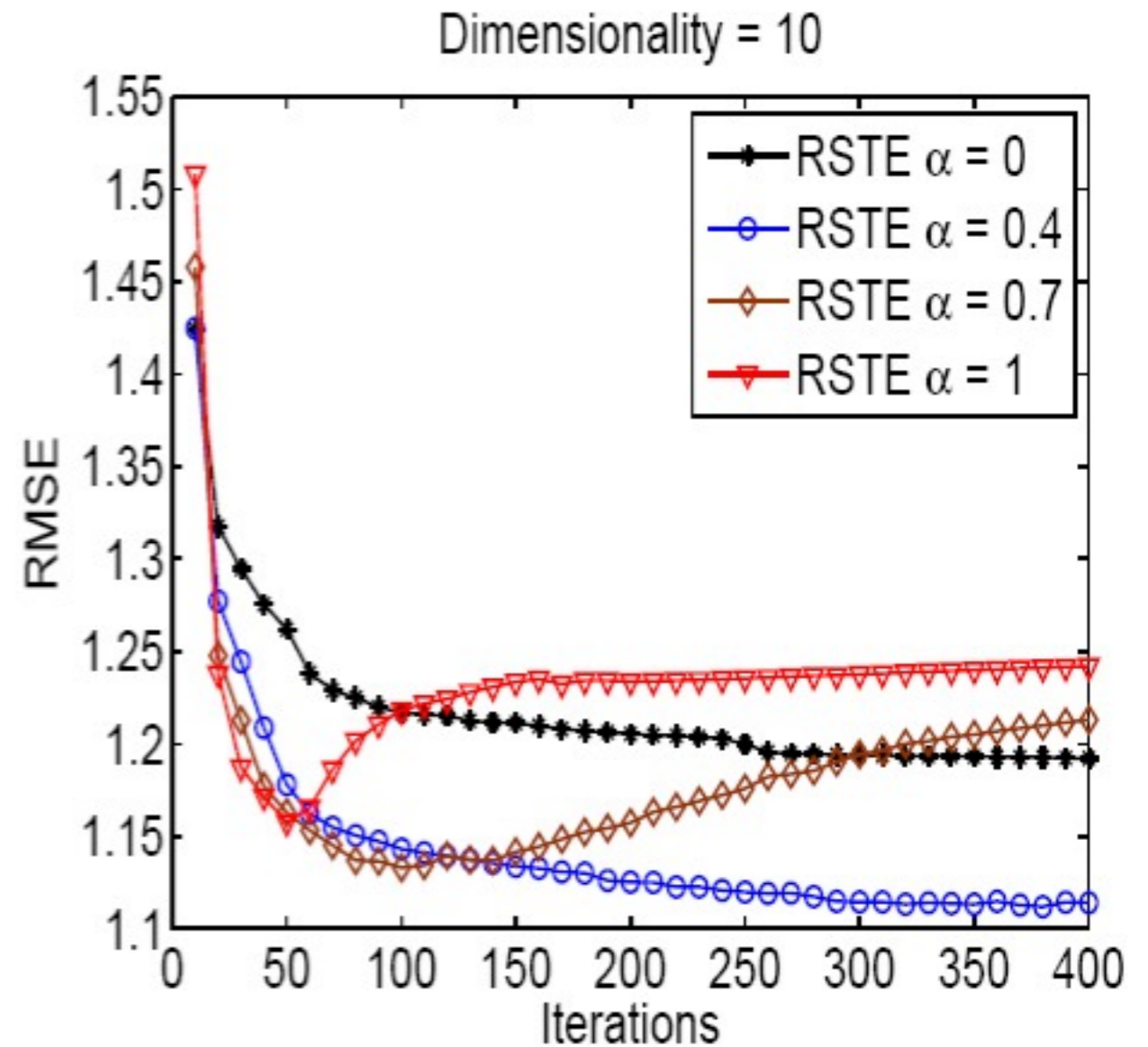
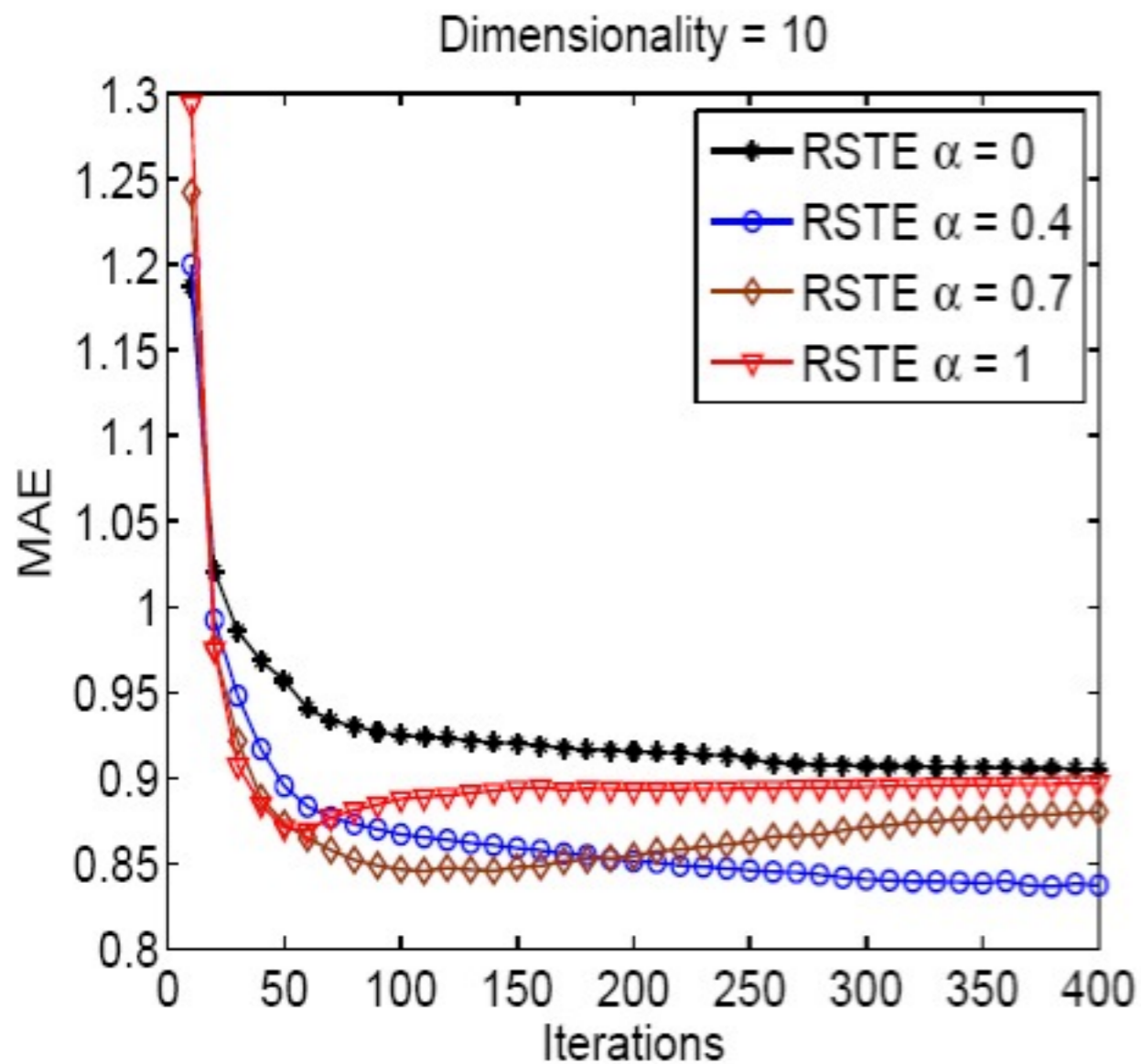
# Impact of Parameter Alpha



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



# MAE and RMSE Changes with Iterations

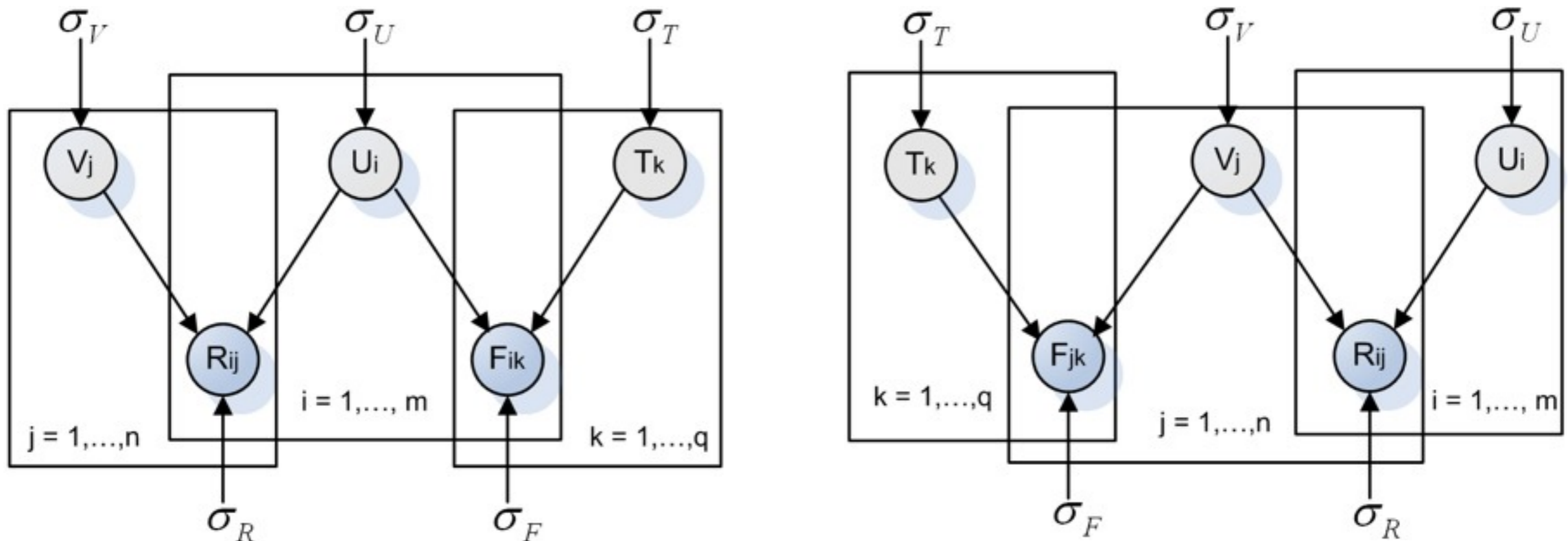


90% as Training Data



# 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	<b>0.6199</b>	<b>0.6407</b>	<b>0.6395</b>	<b>0.7026</b>
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	<b>0.6187</b>	<b>0.6395</b>	<b>0.6584</b>	<b>0.7016</b>



# Further Discussion of SoRec

- RMSE

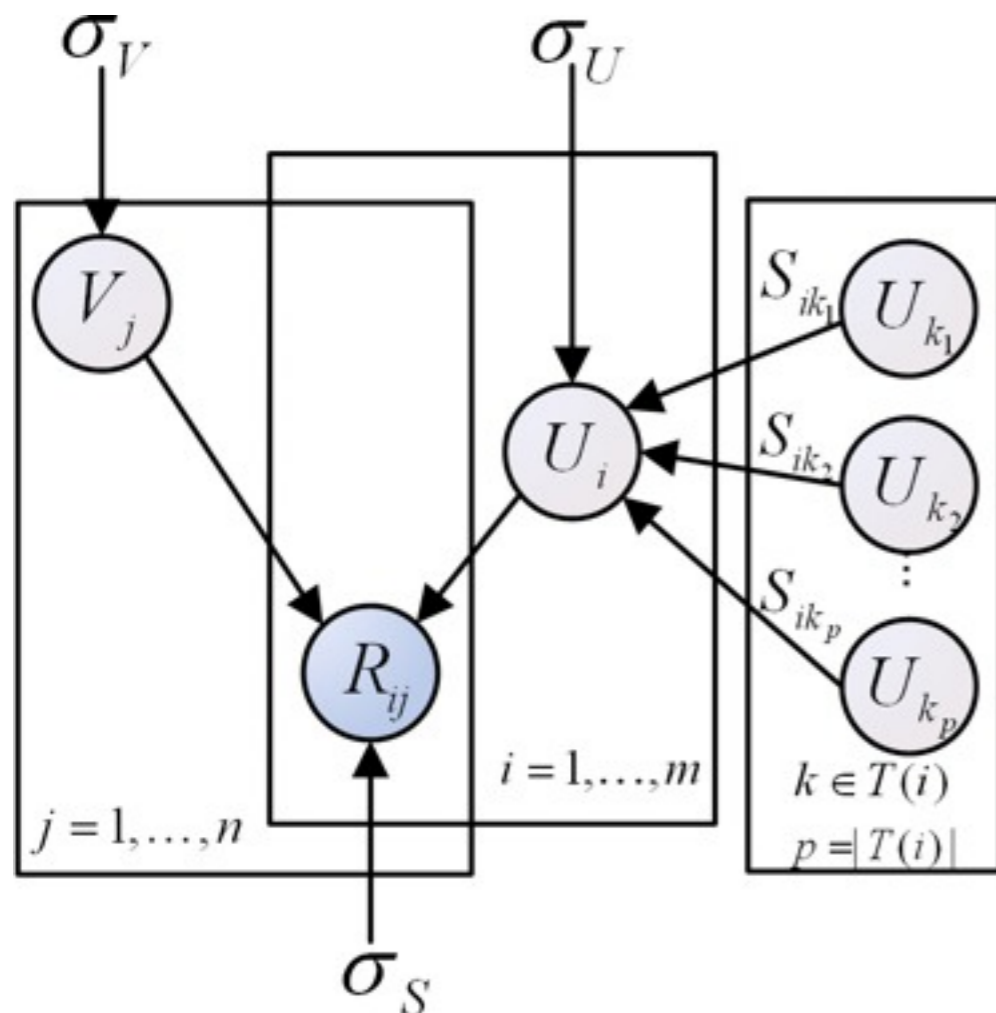
Table VI: RMSE comparison with other approaches on MovieLens dataset (A smaller RMSE value means a better performance)

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	<b>0.8112</b>	<b>0.8370</b>	<b>0.8591</b>	<b>0.9033</b>
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	<b>0.8097</b>	<b>0.8359</b>	<b>0.8578</b>	<b>0.9019</b>



# 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



# Recommend with Social Distrust

[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**
  - **Many** 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  $U_d$ .





# Distrust

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

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



# 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

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

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



# Web Site Recommendation

[Ma et al., SIGIR 2011]





# Traditional Search Paradigm

The image shows a screenshot of a Bing search results page for the query "sigir". The page layout includes a top navigation bar with links for Web, Images, Videos, Shopping, News, Maps, and More, along with user account information for "Irwin" and location "Walnut Creek, California". The search bar contains the text "sigir" and a magnifying glass icon. Below the search bar, there are tabs for "Web", "News", "Images", and "More". The main content area displays search results under the heading "ALL RESULTS" and "1-10 of 255,000 results". The first result is "Welcome to SIGIR | Home" with a description of an Iraqi fisherman and the URL "www.sigir.mil". The second result is "ACM SIGIR Special Interest Group on Information Retrieval Home Page" with a description of the ACM SIGIR website and the URL "www.sigir.org". The third result is "home [ACM SIGIR 2010]" with a description of the 2010 conference and the URL "www.sigir2010.org". The fourth result is "Welcome to The 34th Annual ACM SIGIR Conference" with a description of important dates and the URL "sigir2011.org". The fifth result is "About SIGIR" with a description of the Special Inspector General for Iraq Reconstruction and the URL "www.sigir.mil/about/index.html". The sixth result is "SIGIR 2009 Archive | SIGIR'09" with a description of the 2009 conference and the URL "sigir2009.org". On the left side, there are sections for "RELATED SEARCHES" (including "Special Inspector General for Iraq Reconstruction", "SIGIR Reports", "SIGIR Poster", "SIGIR List", "SIGIR 2011", "SIGIR 10", "SIGIR 2010 Registration", "SIGIR 2009 Proceedings"), "SEARCH HISTORY" (with a link to "Search more to see your history"), and "NARROW BY DATE" (with options for "All results", "Past 24 hours", "Past week", and "Past month"). On the right side, there is a "Bing Rewards" section with the text "Earn Rewards with Bing" and "Join Bing Rewards for free and earn 250 credits."





# “Search” to “Discovery”



News Corp.  
Windows 8 iPhone 5  
How to cook?

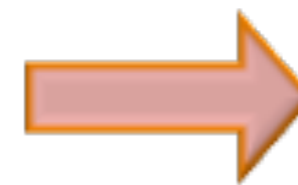


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News Corp.  
Windows 8 iPhone 5  
How to cook?



# Challenges in Web Site Recommendation

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

		Queries				
		$z_1$	$z_2$	$z_3$	$z_4$	$z_5$
Web users	$u_1$	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

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

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

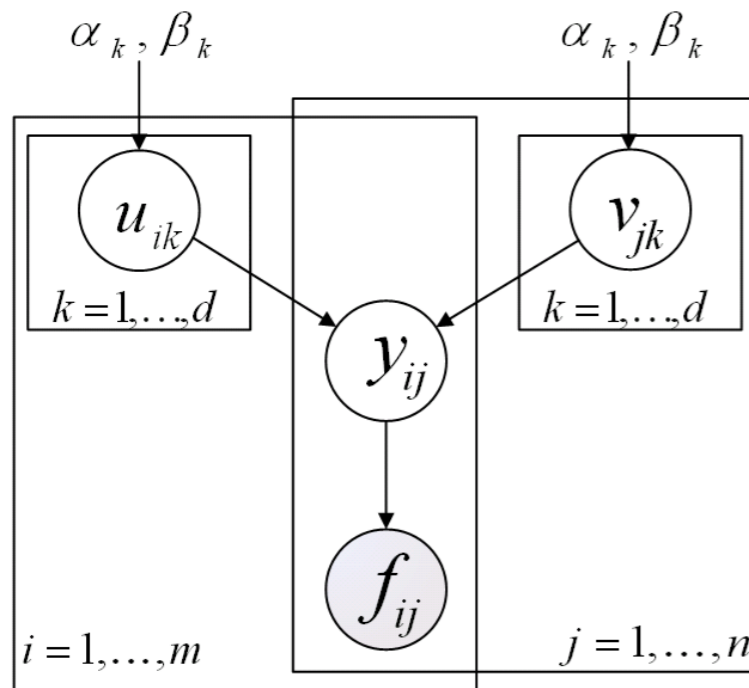
$$p(U | \sigma_U^2) = \prod_{i=1}^m \mathcal{N}(U_i | 0, \sigma_U^2 \mathbf{I})$$

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





# Probabilistic Factor Model



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  $f_{ij} \sim \text{Poisson}(y_{ij})$ .

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

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

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

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

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



# Probabilistic Factor Model

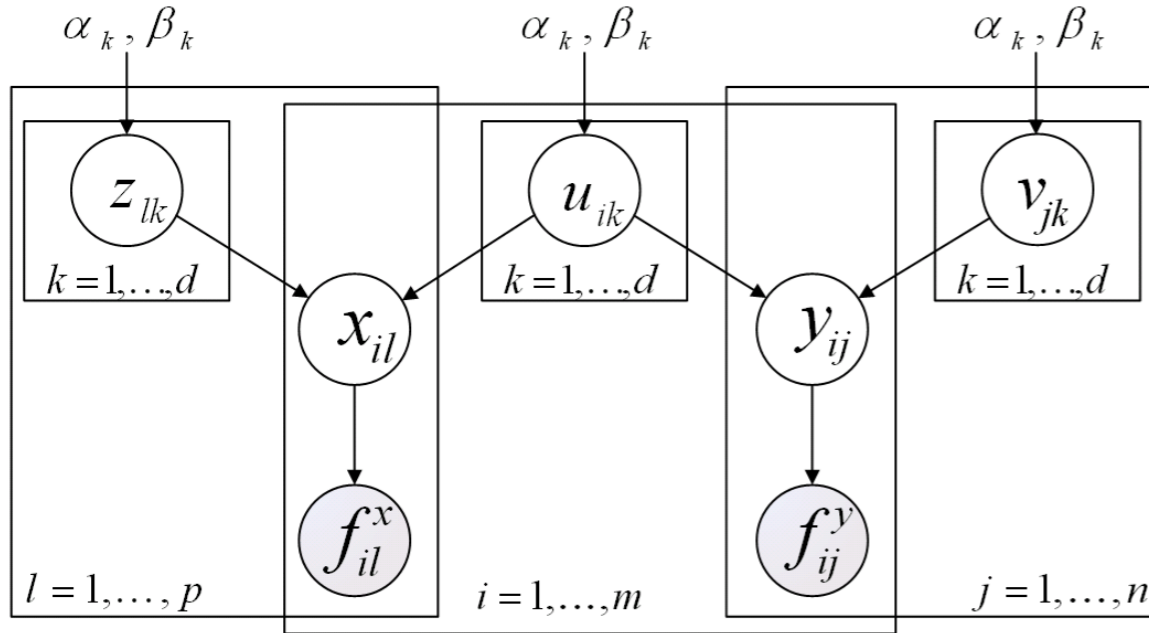
$$\begin{aligned}\mathcal{L}(U, V; F) &= \sum_{i=1}^m \sum_{k=1}^d ((\alpha_k - 1) \ln(u_{ik}/\beta_k) - u_{ik}/\beta_k) \\ &+ \sum_{j=1}^n \sum_{k=1}^d ((\alpha_k - 1) \ln(v_{jk}/\beta_k) - v_{jk}/\beta_k) \\ &+ \sum_{i=1}^m \sum_{j=1}^n (f_{ij} \ln y_{ij} - y_{ij}) + \text{const.}\end{aligned}$$

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

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



# Collective Probabilistic Factor Model



$$\mathcal{L}(U, V, Z; F^x, F^y)$$

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

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

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

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

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



# 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
- In user-site frequency matrix 2,612,016 entries, while in user-query frequency matrix 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 Improve	2.246 80.98%	1.094 60.96%	0.488 12.50%	0.476 10.29%	0.465 8.17%	0.440 2.95%	0.432	<b>0.427</b>
	NRMSE Improve	3.522 85.24%	2.171 76.05%	0.581 10.50%	0.570 8.77%	0.554 6.14%	0.532 2.26%	0.529	<b>0.520</b>
80%	NMAE Improve	2.252 80.99%	1.096 60.95%	0.490 12.65%	0.478 10.46%	0.468 8.55%	0.441 2.95%	0.434	<b>0.428</b>
	NRMSE Improve	3.714 86.00%	2.159 75.91%	0.584 10.96%	0.571 8.93%	0.560 7.14%	0.533 2.44%	0.530	<b>0.520</b>





# Impact of Parameters

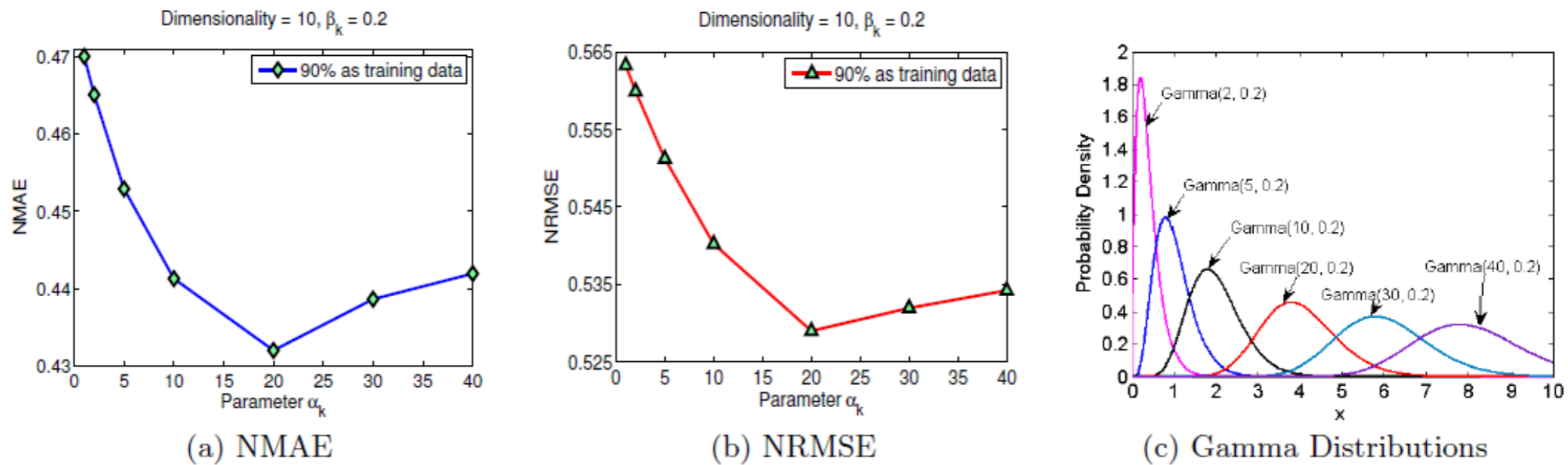


Figure 6: Impact of Parameter  $\alpha_k$  in PFM

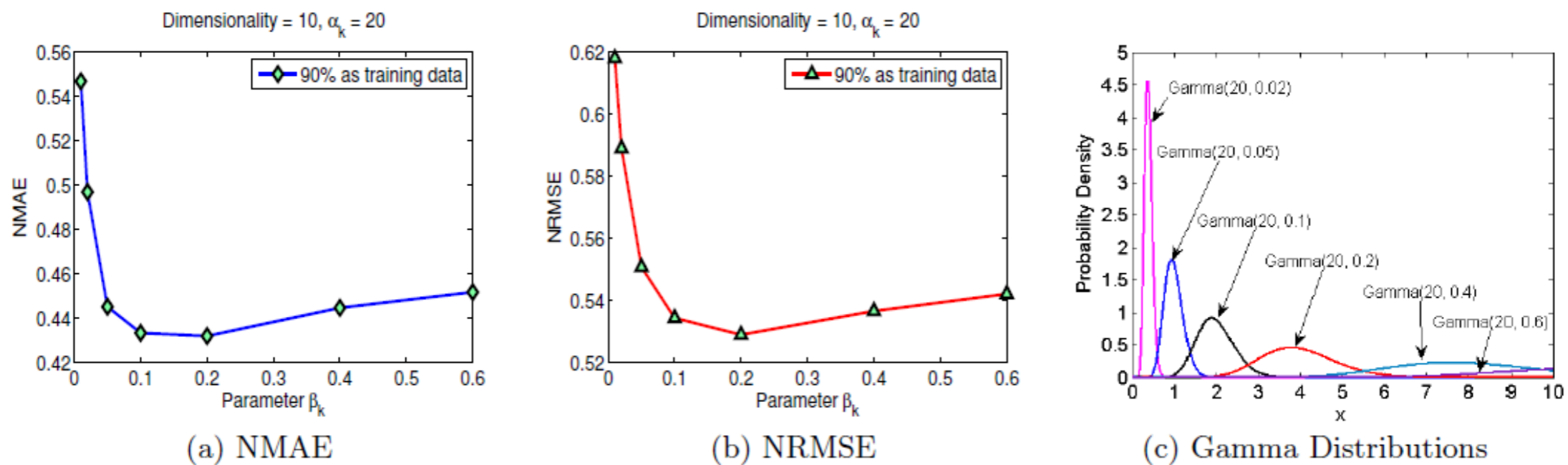
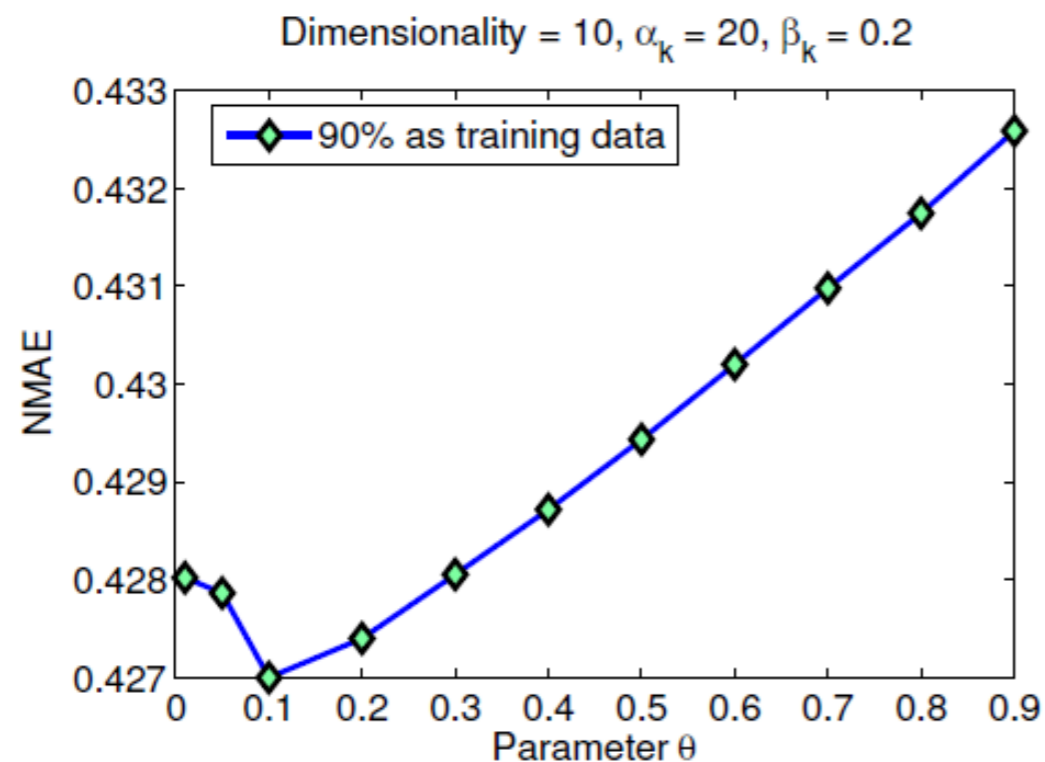


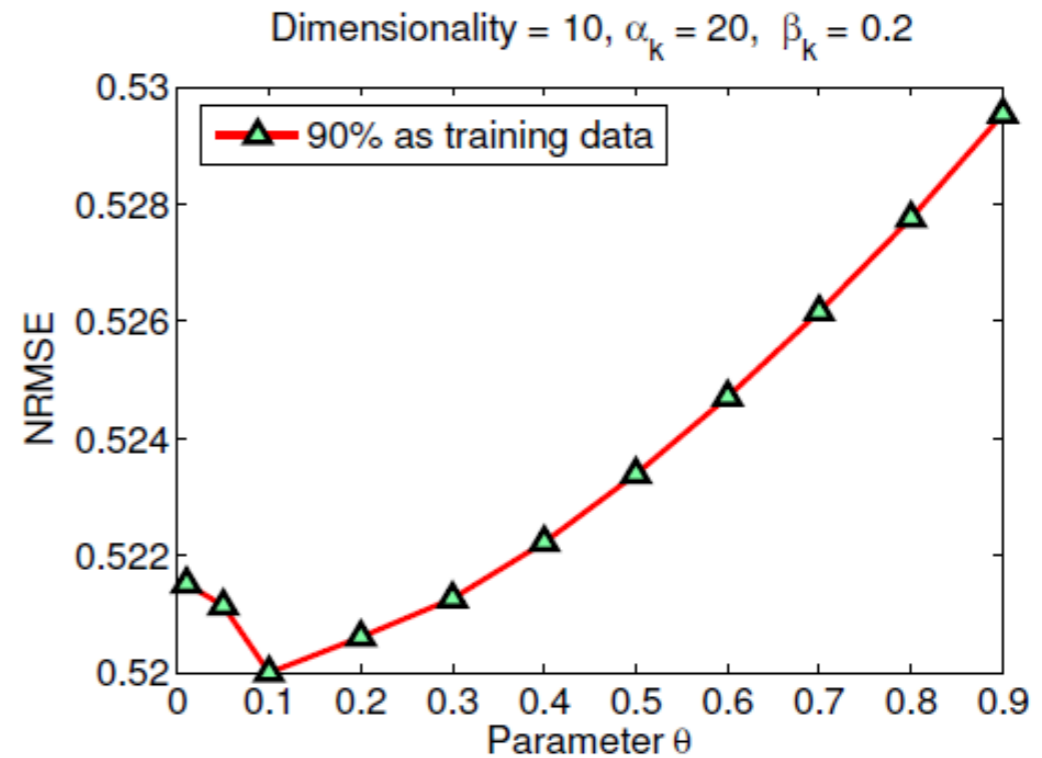
Figure 7: Impact of Parameter  $\beta_k$  in PFM



# Impact of Parameters



(a) NMAE



(b) NRMSE

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

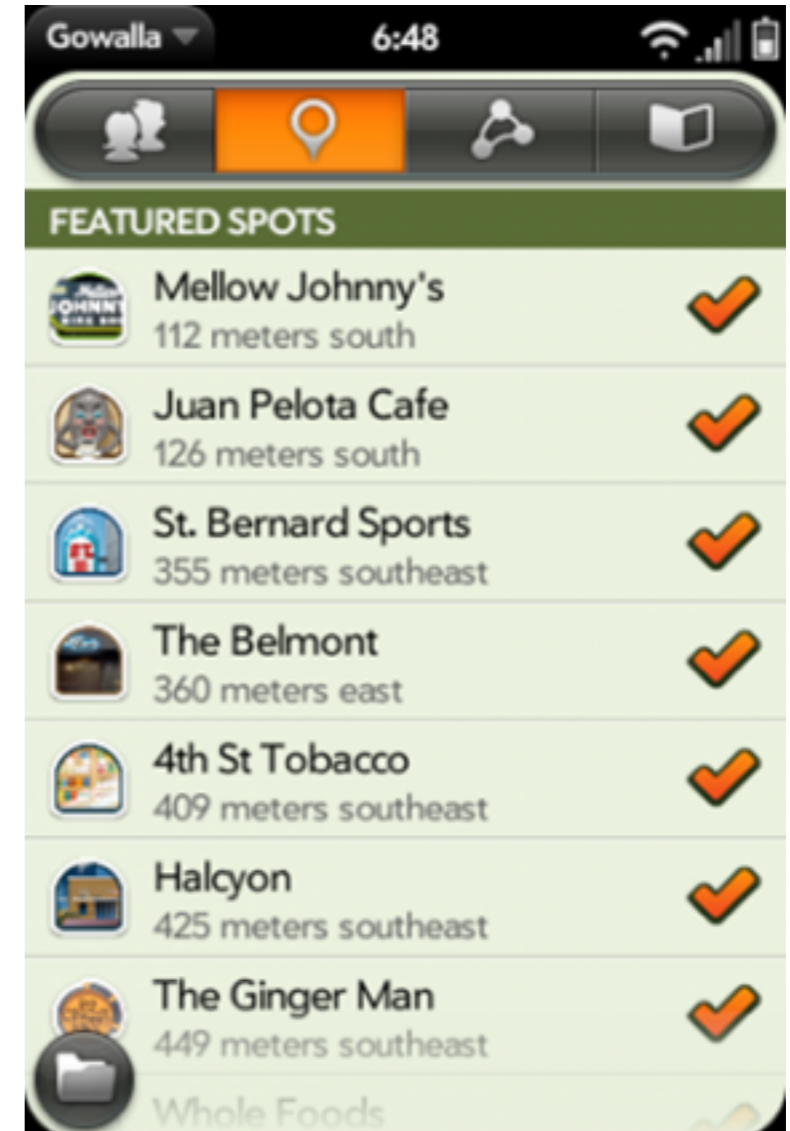


# Location Recommendations

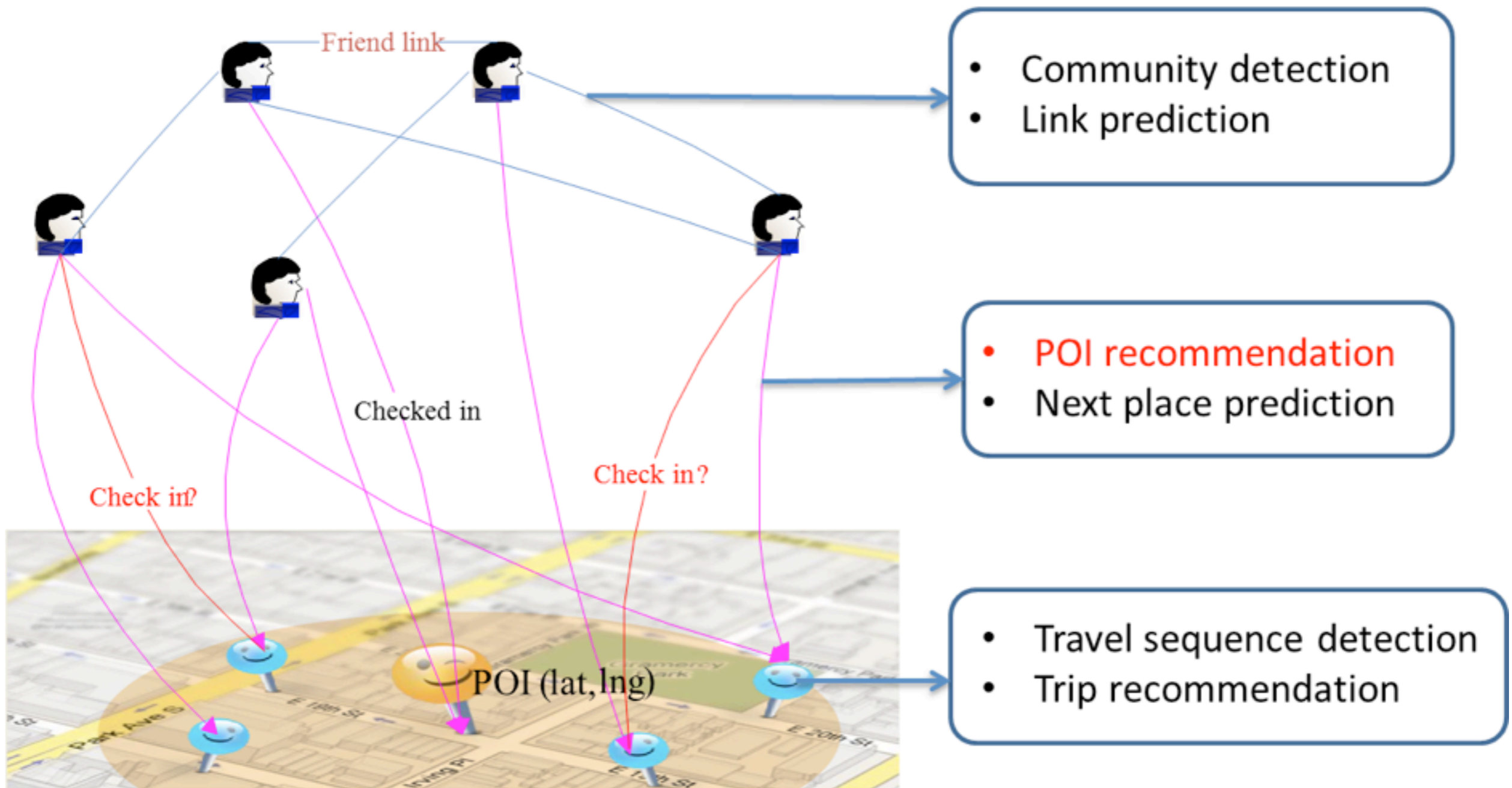
[Cheng et al., AAI 2012]



# Check Out on “Check-ins”



# Location-based Social Networks (LBSNs)





# Related Work

- POI recommendation on GPS trajectory logs
  - A collective matrix factorization method is applied on three matrices: location-activity, location-feature and activity-activity. [Zheng et al. 2010a]
  - A tensor factorization is conducted on the user-location-activity relationship. [Zheng et al. 2010b]
- POI recommendation on LBSNs dataset
  - A unified memory-based framework including user similarity, social and geographical influence, in which geographical influence is modeled as power-law distribution. [Ye et al. 2011]
  - Two-center mixture Gaussian model proposed to model human mobility in LBSNs. [Cho et al. 2011]



# Motivations

- Users have their **personalized taste** for different POIs.

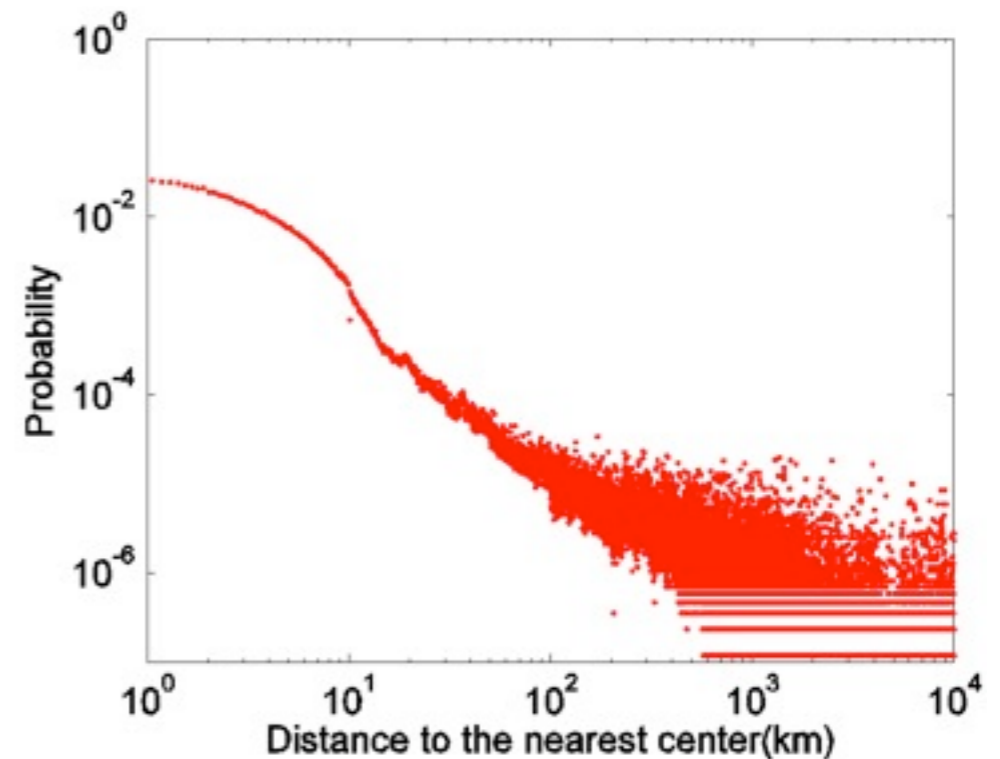
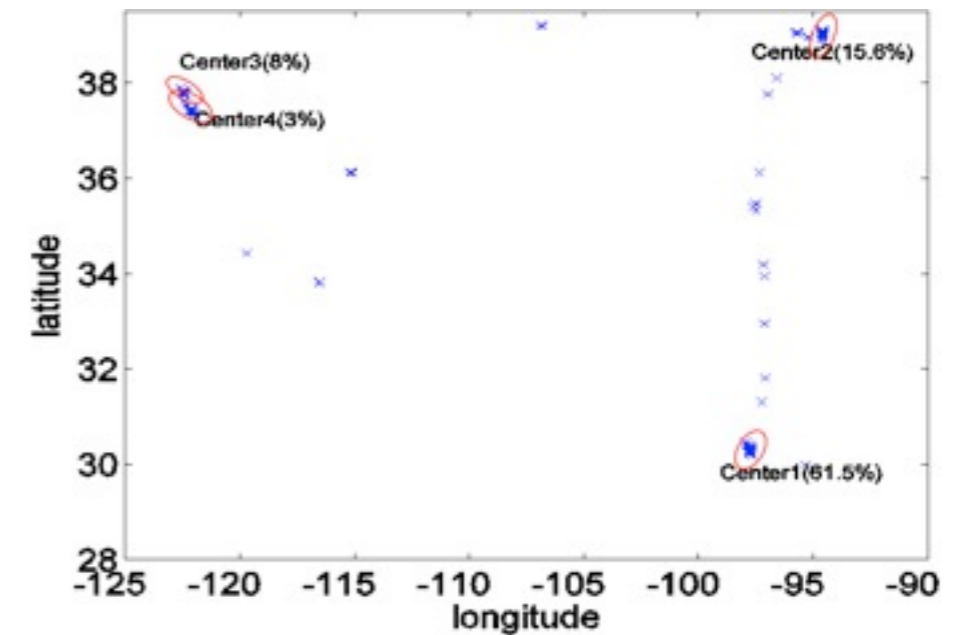


- The check-in probability is sensitive to **geographical influence**.



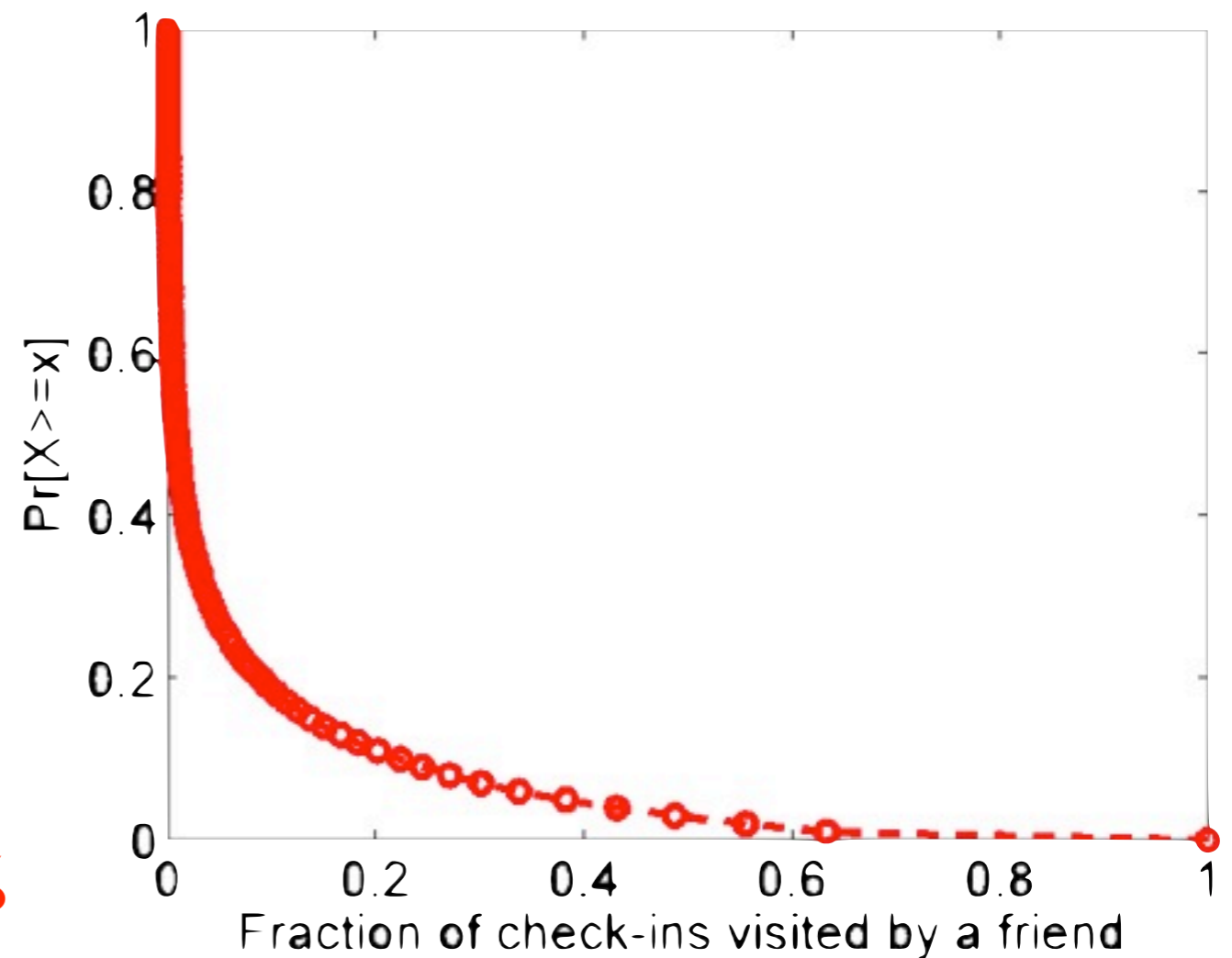
# Observation #1

- Users tend to check-in around several centers
- Gaussian distribution to model check-ins at each center
- Inverse Distance Rule: check-in probability is inversely proportional to the distance to the nearest center



# Observation #2

- Social information can help improve POI recommendation, but seems influence is limited
- On average, overlap of a user's check-ins to his friends only about **9.6%**
- **90%** users have only **20%** common check-ins



# Our Proposal

- Multi-center Gaussian Model (**MGM**) to capture geographical influence
- Propose a generalized **fused matrix factorization framework** to include social and geographical influences
- **Experiments** conducted on large-scale Gowalla dataset





# Multi-center Gaussian Model

- Notations

- $C_u$ : multi-center set for user  $u$
- $f_{c_u}$ : total frequency at center  $c_u$  for user  $u$
- $\mathcal{N}(l|\mu_{c_u}, \Sigma_{c_u})$ : the pdf of Gaussian distribution,  $\mu_{c_u}$  and  $\Sigma_{c_u}$  denote the mean and covariance matrices of regions around center  $c_u$

- The probability a user  $u$  visiting a location  $l$  given  $C_u$  is defined as:

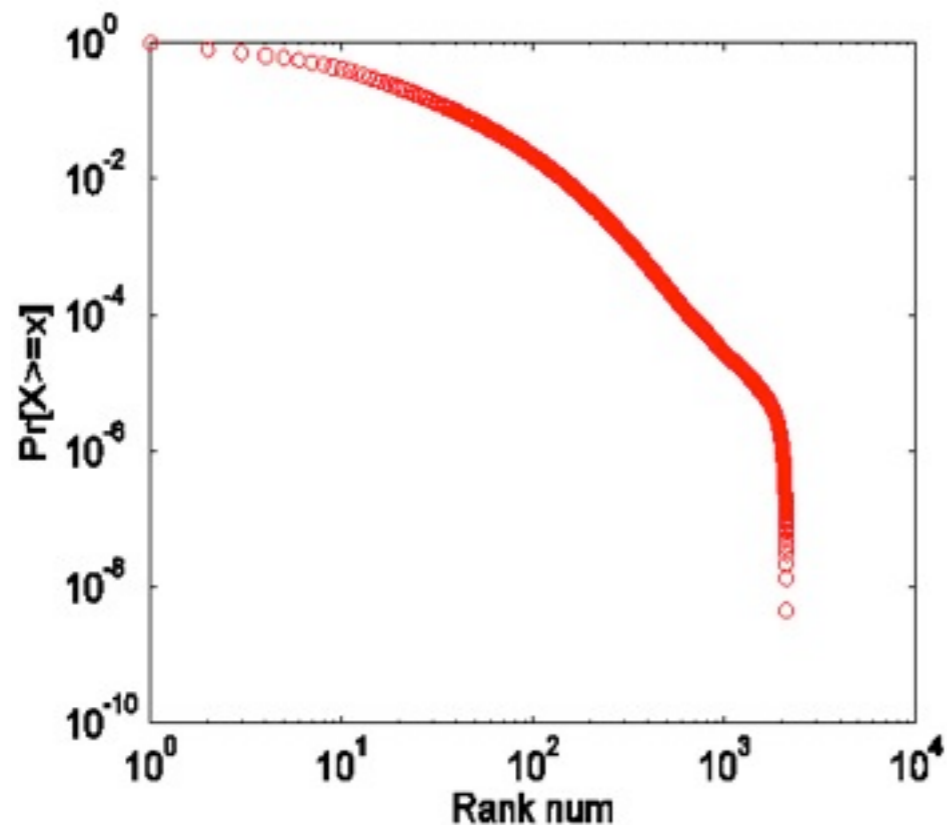
$$P(l|C_u) = \sum_{c_u=1}^{|C_u|} P(l \in c_u) \frac{f_{c_u}^\alpha}{\sum_{i \in C_u} f_i^\alpha} \frac{\mathcal{N}(l|\mu_{c_u}, \Sigma_{c_u})}{\sum_{i \in C_u} \mathcal{N}(l|\mu_i, \Sigma_i)}.$$

Which center?      Frequency normalization      Gaussian distribution of the center



# Multi-center Discovery Algorithm

- A greedy clustering algorithm is proposed due to Pareto principle (top 20 locations cover about 80% check-ins)



```
1: for all user  $i$  in the user set  $\mathcal{U}$  do
2:   Rank all check-in locations in  $|\mathcal{L}|$  according to visiting frequency
3:    $\forall l_k \in L$ , set  $l_k.center = -1$ ;
4:   Center_list =  $\emptyset$ ; center_no = 0;
5:   for  $i = 1 \rightarrow |L|$  do
6:     if  $l_i.center == -1$  then
7:       center_no++; Center =  $\emptyset$ ; Center.total_freq = 0;
8:       Center.add( $l_i$ ); Center.total_freq +=  $l_i.freq$ ;
9:       for  $j = i + 1 \rightarrow |L|$  do
10:        if  $l_j.center == -1$  and  $dist(l_i, l_j) \leq d$  then
11:           $l_j.center = center\_no$ ; Center.add( $l_j$ );
12:          Center.total_freq +=  $l_j.freq$ ;
13:        end if
14:      end for
15:      if Center.total_freq  $\geq |u_i|.total\_freq * \theta$  then
16:        Center_list.add(Center);
17:      end if
18:    end if
19:  end for
20:  RETURN Center_list for user  $i$ ;
```



# Fused Framework

- Probabilistic Matrix Factorization (PMF) models users' **preference** on locations:  $F \approx U^T L$ , and the frequency will be converted to  $[0, 1]$  by  $g(x) = 1/(1 + \exp(-x))$ .
- PFM with **Social Regularization** (PMFSR) [Ma et al. 2011b]:

$$\begin{aligned} \min_{U,L} \Omega(U, L) &= \sum_{i=1}^{|\mathcal{U}|} \sum_{j=1}^{|\mathcal{L}|} I_{ij} (F_{ij} - U_i^T L_j)^2 \\ &+ \beta \sum_{i=1}^{|\mathcal{U}|} \sum_{f \in \mathcal{F}(i)} \text{Sim}(i, f) \|U_i - U_f\|_F^2 \\ &+ \lambda_1 \|U\|_F^2 + \lambda_2 \|L\|_F^2, \end{aligned}$$

- MGM models **geographical influence**
- We can fuse them together:

$$P_{ul} = \lambda P(F_{ul}) + (1 - \lambda) P(l|C_u), \text{ where } P(F_{ul}) \propto U_u^T L_l.$$

---

Social  
Influence

---

Geographical  
Influence

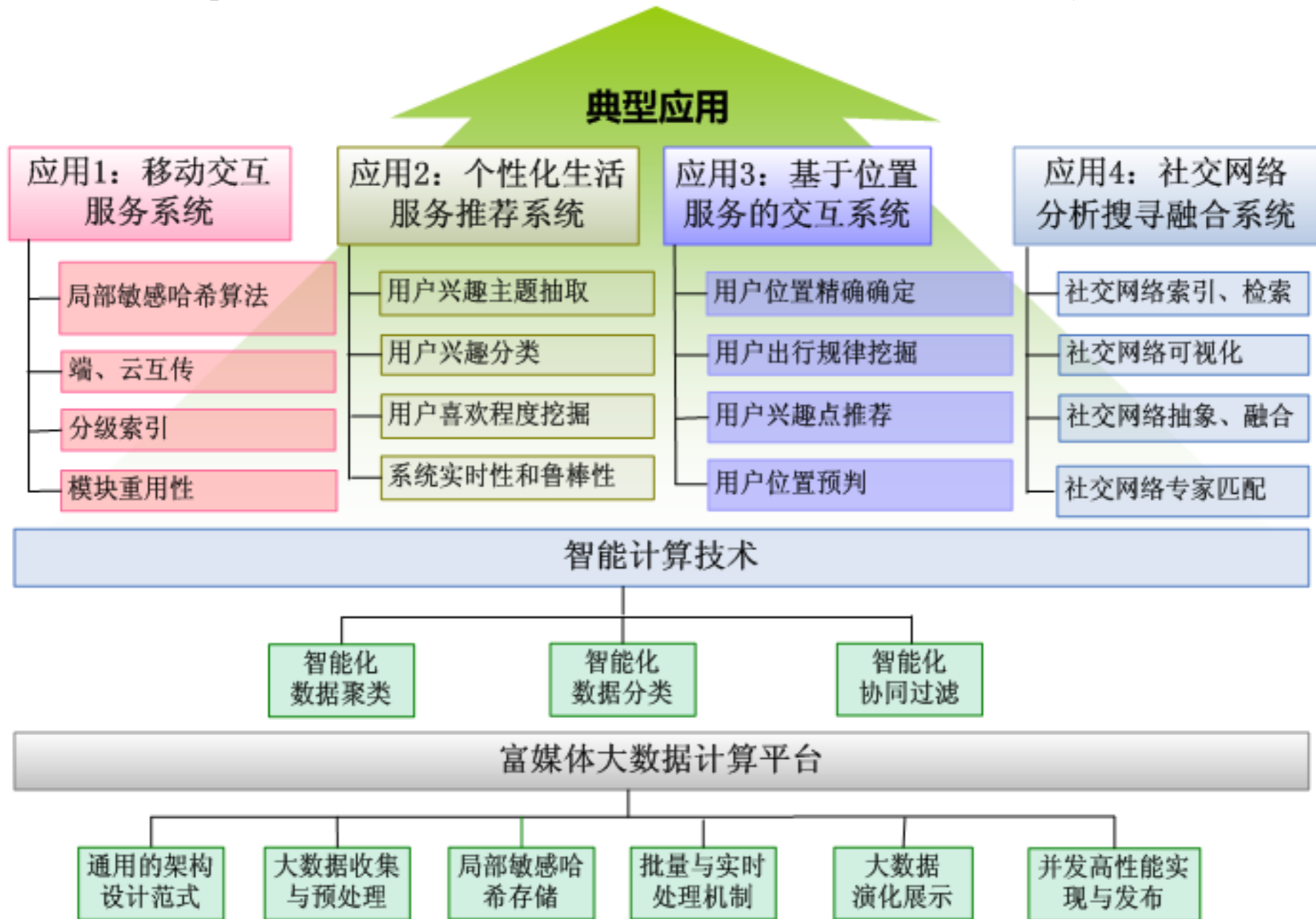


# Concluding Remarks

- Both social and location recommendation play a significant role in the social web!
- **Social recommendation** extends traditional models and techniques by using **social graphs, ensembles, distrust relationships, clicks**, etc.
- Fusing of social behavior information, e.g., media consumption patterns, temporal relationships, etc.
- **Location recommendation** follows a similar path with new **data** and **features**.



# 深圳市富媒体大数据重点实验室





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## ACM RecSys 2013

The ACM Recommender System conference is the premier international forum for the presentation of new research results, systems and techniques in the broad field of recommender systems. Recommendation is a particular form of information filtering, that exploits past behaviours and user similarities to generate a list of information items that is personally tailored to an end-user's preferences. The seventh conference in this series, RecSys 2013, will bring together researchers and practitioners from academia and industry to present the latest results and identify new trends and challenges in providing recommendation components in a range of innovative application contexts. As RecSys brings together the main international research groups working on recommender systems, along with many of the world's leading e-commerce companies, in the last number of years, it has become the most important annual conference for the presentation and discussion of recommender system research. In addition to the main technical track, RecSys 2013 program will feature keynote and invited talks, tutorials covering state-of-the-art in this domain, a workshop program, an industrial track and a doctoral symposium.

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Recent Developments in Social and Location Recommendations, Irwin King  
CCFADL 39 on Social Networks and Analysis, August 3-5, 2013, Beijing, China



# CrowdRec 2013

Workshop on Crowdsourcing and Human Computation for Recommender Systems

Co-located with ACM RecSys 2013, Hong Kong, 12th October, 2013

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## Announcements

**2013-07-18**

The deadline of submission has been extended to 26th July, 2013.

**2013-05-24**

CrowdRec 2013 Website launched.

## Introduction

We are pleased to announce the first workshop on crowdsourcing and human computation for recommender systems. The recommender systems we refer to as a broad spectrum of applications involving recommendation, information valuation, filtering, summarization, etc. in various contexts from e-commerce to social networking and mobile applications. This workshop aims to provide a scholarly venue for researchers and practitioners to exchange the advances of crowdsourcing and human computation technologies and applications, with an emphasis on the applications in recommendation systems. The potentials and advantages of crowdsourcing and human computation have been explored for a number of areas such as computer-human interaction and information retrieval, we believe that these advances can also benefit the research of recommender systems at large.

## Call For Papers

### Important Dates

**26th July, 2013 (PDT)**  
Submission due (**Extended**)

**16th August, 2013**  
Author notification

**30th August, 2013**  
Camera-ready version due

**12th October, 2013**  
CrowdRec 2013 Workshop

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In conjunction with the 2013 IEEE International Conference on Big Data (**IEEE Big Data 2013**)

# Workshop on Scalable Machine Learning: Theory and Applications

**October 6, 2013, Santa Clara, CA, USA**

Big Data are encountered in various areas, including Internet search, social networks, finance, business sectors, meteorology, genomics, connectomics, complex physics simulations, and biological and environmental research. The huge volume, high velocity, significant variety, and low veracity bring challenges to current machine learning techniques. It is desirable to scale up machine learning techniques for modeling and analyzing the big data from various domains.

The workshop aims to provide professionals, researchers, and technologists with a single forum where they can discuss and share the state-of-the-art of *scalable machine learning* technologies from theory and applications.

We thank the following experts for accepting our invitation to give plenary talks:

- [Mikhail Bilenko](#), Microsoft research
- [Carlos Guestrin](#), University of Washington
- Alek Kolcz, Twitter
- [Alex Smola](#), Carnegie Mellon University

## Topics of Interest

Topics of interest include, but not limited to:

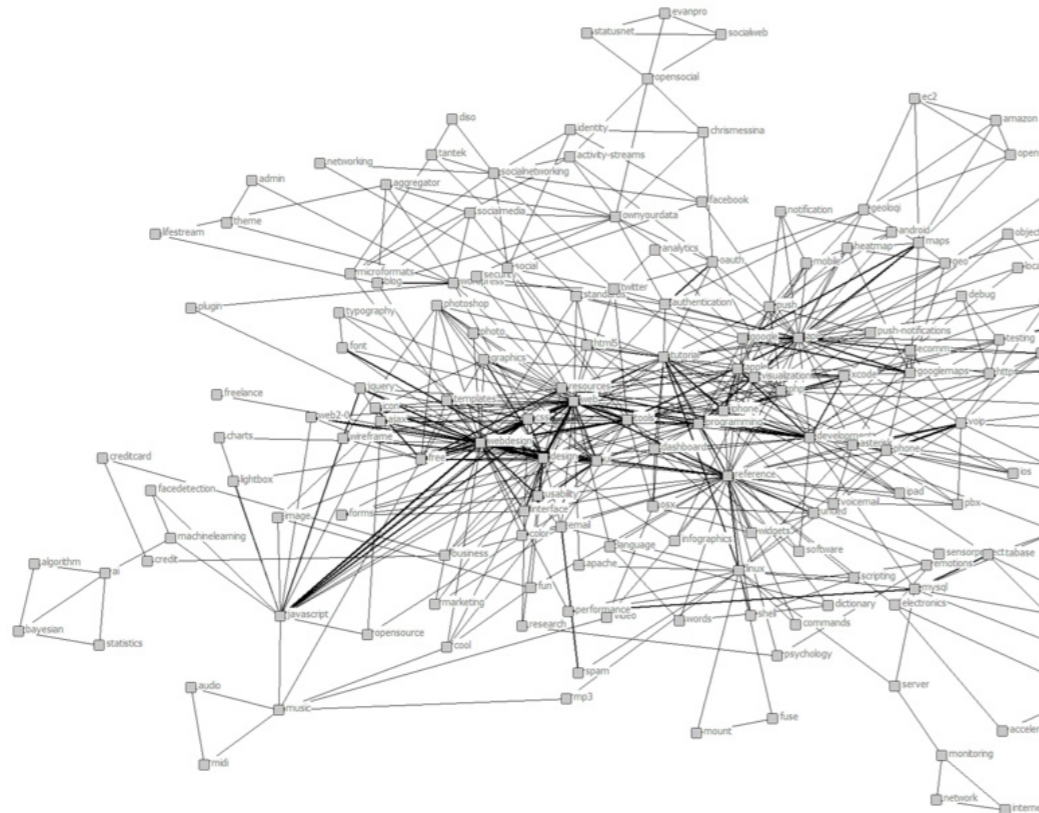
- **Distributed machine learning architectures**
  - Data separation and integration techniques
  - Machine learning algorithms for GPUs
  - Machine learning algorithms for clouds
  - Machine learning algorithms for clusters

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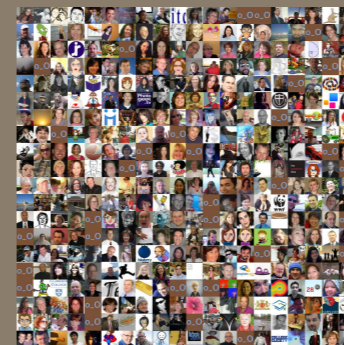


[Irwin King](#)

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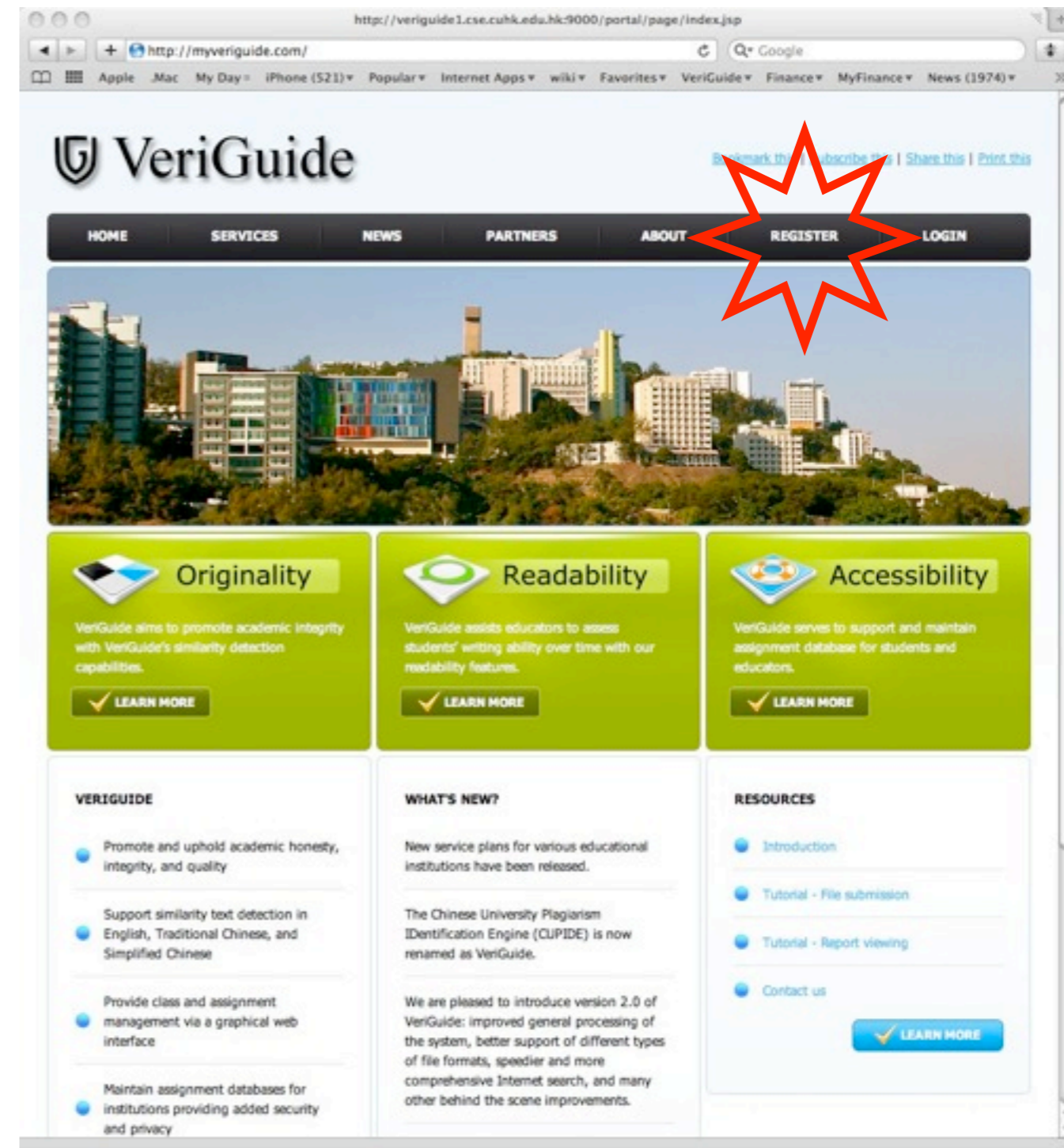
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- **Similarity text** detection system
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- Promote and uphold academic **honesty, integrity, and quality**
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- Handle **.doc, .txt, .pdf, .html,** etc. file formats
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- Associate Editor of INNS Natural Intelligence Magazine ([INNS NIM](#))
- Associate Editor of IEEE Transactions on Neural Networks ([IEEE TNN](#))
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- Chair, SIG and Regional Chapters Committee for Asia and the Pacific ([INNS](#))
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CCF ADL 39 on Social Networks and Mining, August 3-5, 2013, Beijing, China



# Acknowledgments

- Shouyuan Chan (Ph.D.)
- Chen Cheng (Ph.D.)
- Baichuan Li (Ph.D.)
- Guang Ling (Ph.D.)
- Haiqin Yang (Postdoc)
- Connie Yuen (Ph.D.)
- Hongyi Zhang (Ph.D.)
- Chao Zhou (Ph.D.)
- Patrick Lau
- Raymond Yeung







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# Q & A

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