Social Recommendation

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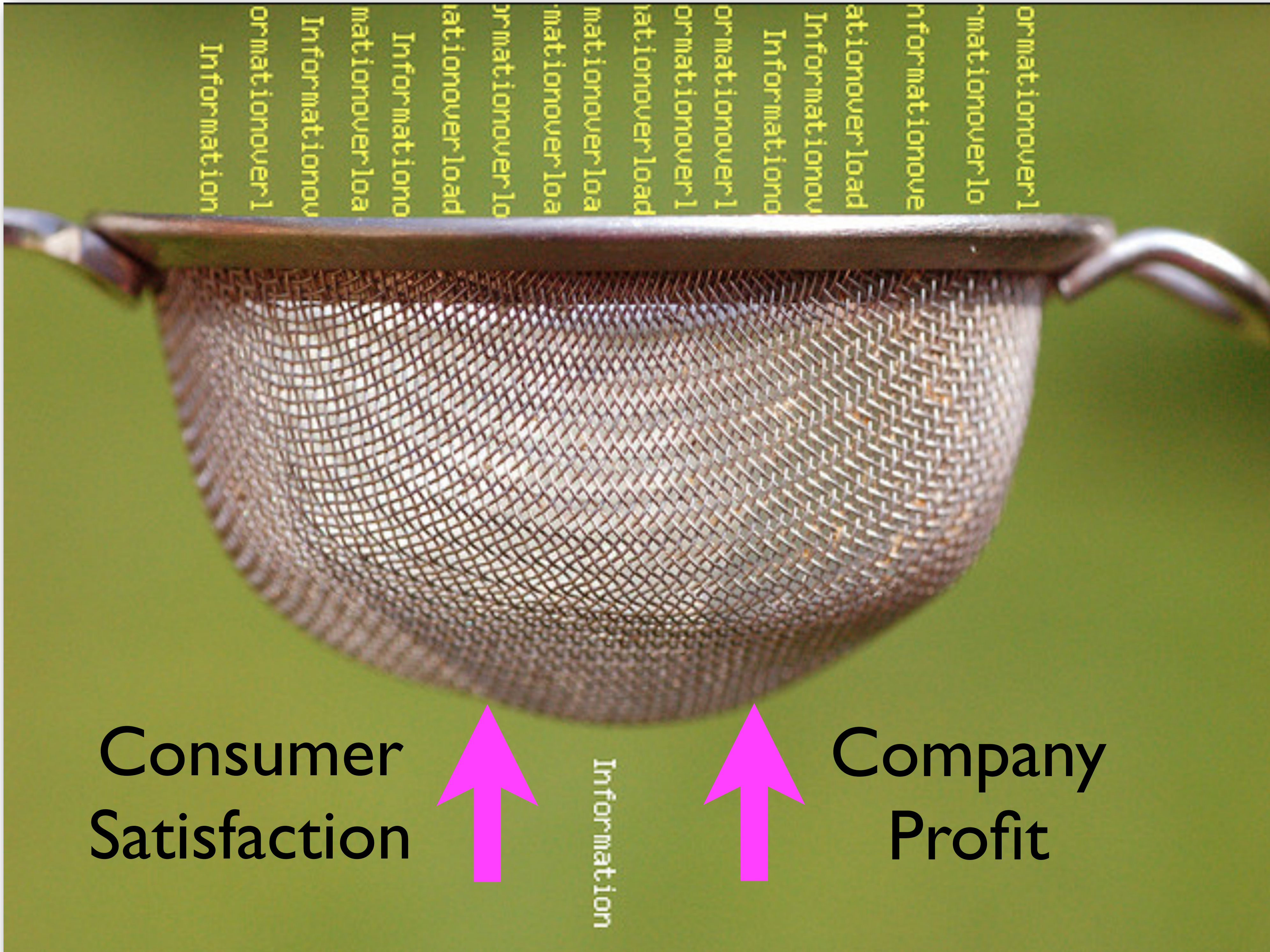
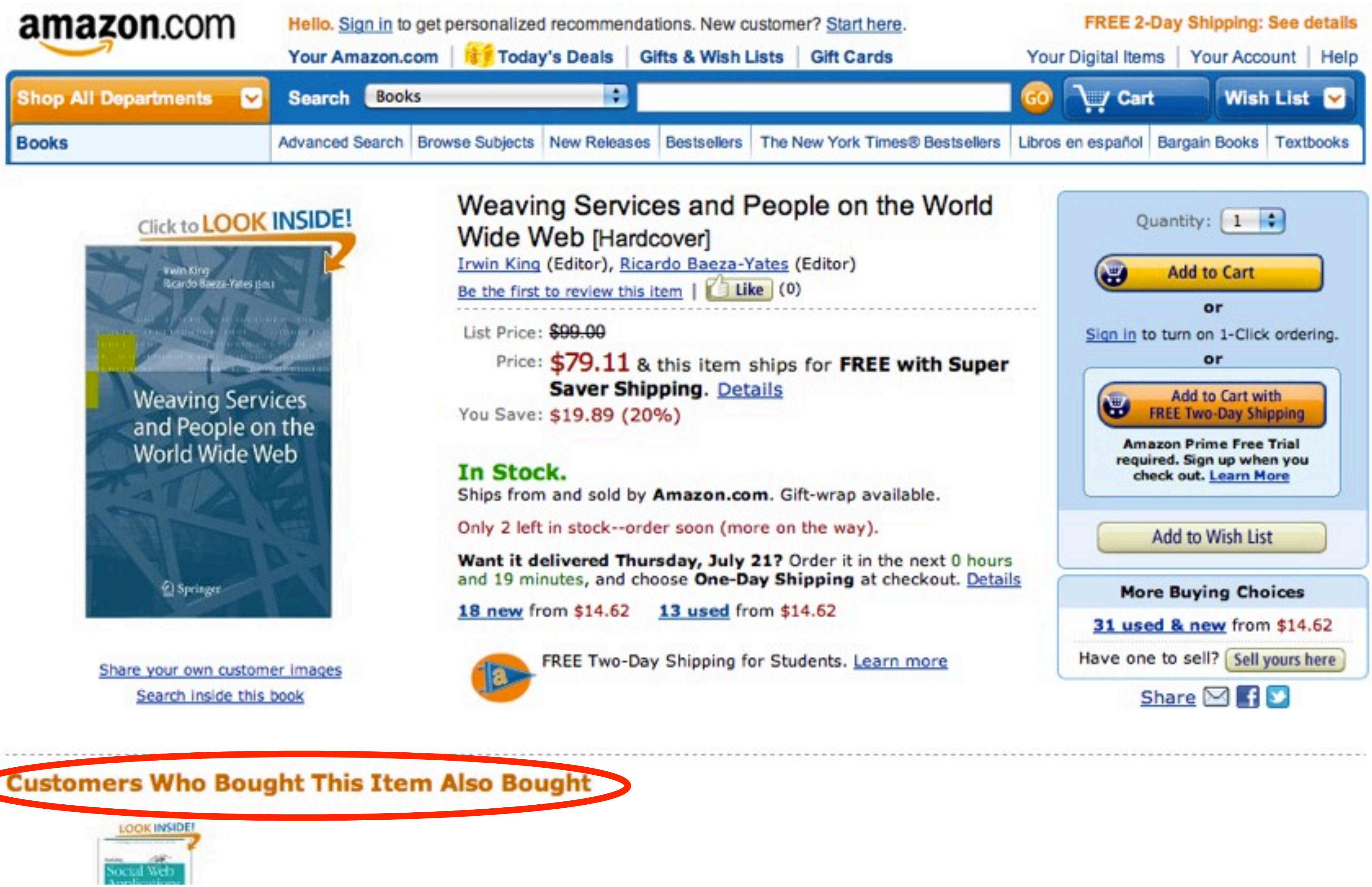
Information and more Information!


Consumer
Satisfaction
Information
Company
Profit

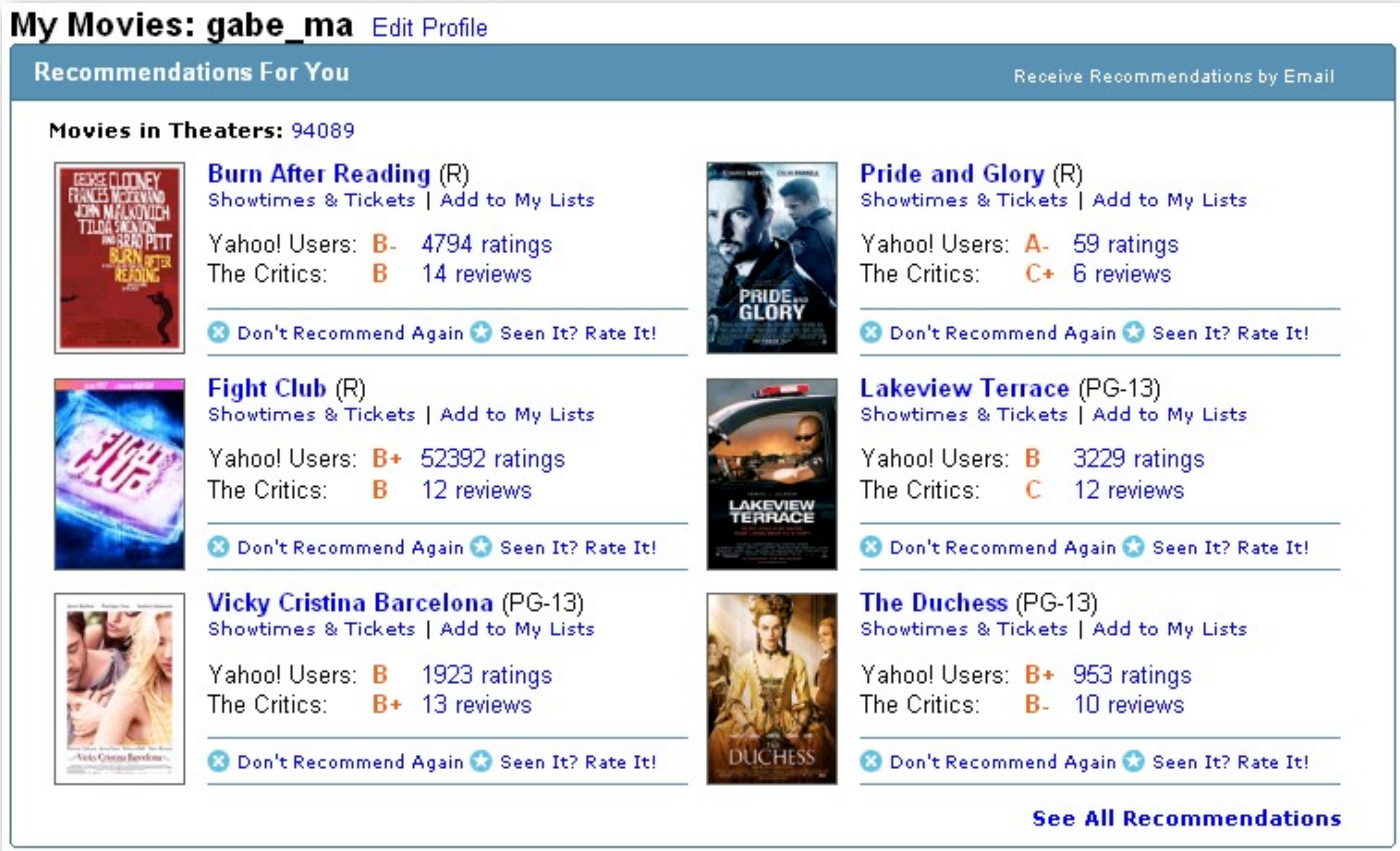
Real Life Examples



Real Life Examples

Real Life Examples

YAHOO! MOVIES



On The Menu

- Introduction
- Basic Techniques
    - Collaborative filtering
    - Matrix factorization
- Different Models
    - Social graph
    - Social ensemble
    - Social distrust
    - Website recommendation

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 the similar users prefer!

Framework

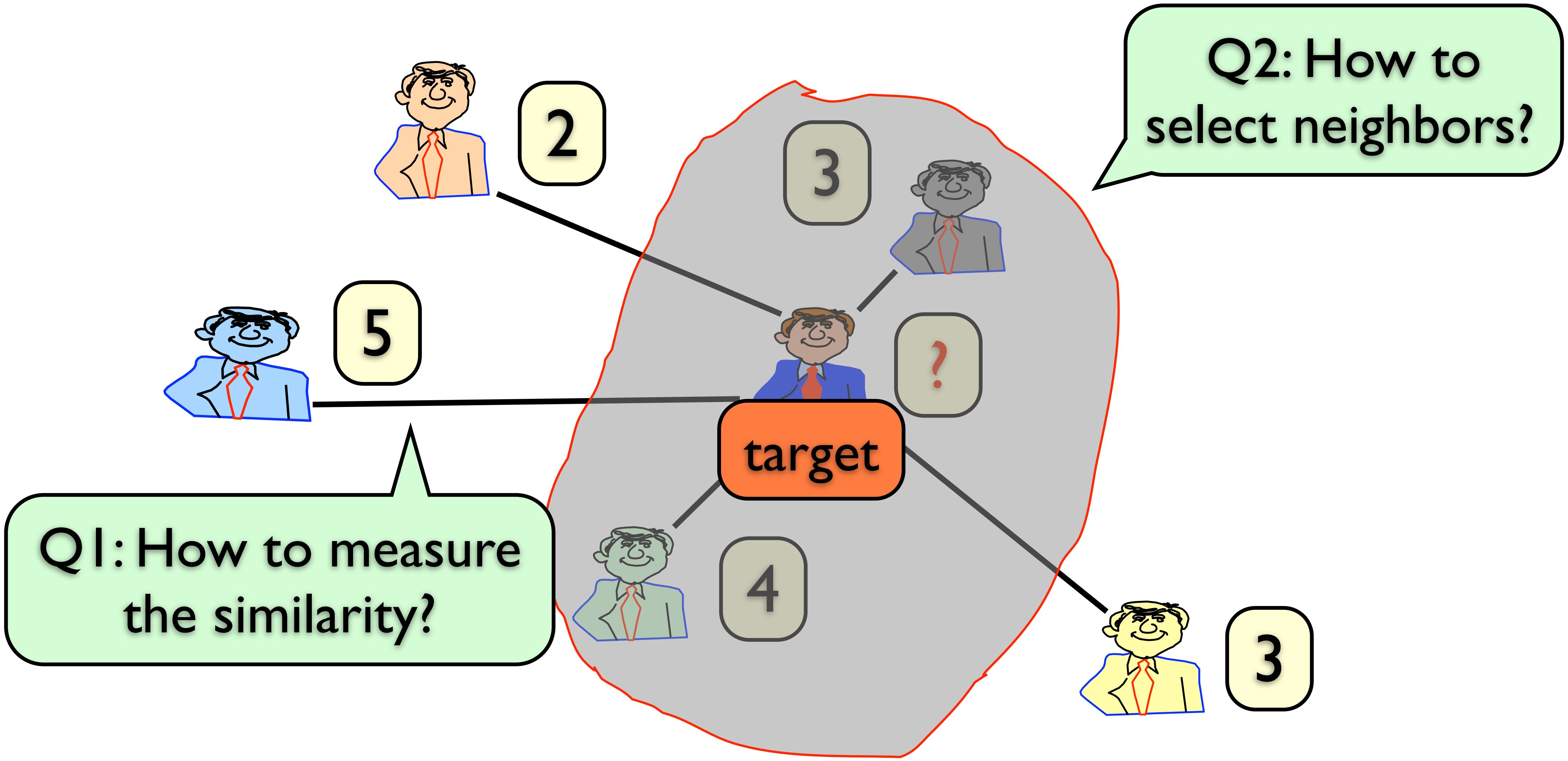
Items

Users

	i_1	i_2				i_j							i_m
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(s) should be recommended?

User-User Similarity



User-based Collaborative Filtering

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	

User-based Collaborative Filtering

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	

User-based Collaborative Filtering

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	

User-based Collaborative Filtering

Items

Users													
u1													
u2	1	3		4		2		5			3	4	
u3													
u4		3		4			3	4		3	4		4
u5													
u6	1			3	5	2		4	1			3	

User-based Collaborative Filtering

Items

Users

u1													
u2	1	$\boxed{3}$		4		2		5			3	4	
u3													
u4		$\boxed{3}$		4			3	4		3	4		4
u5													
u6	1	$\boxed{}$		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]

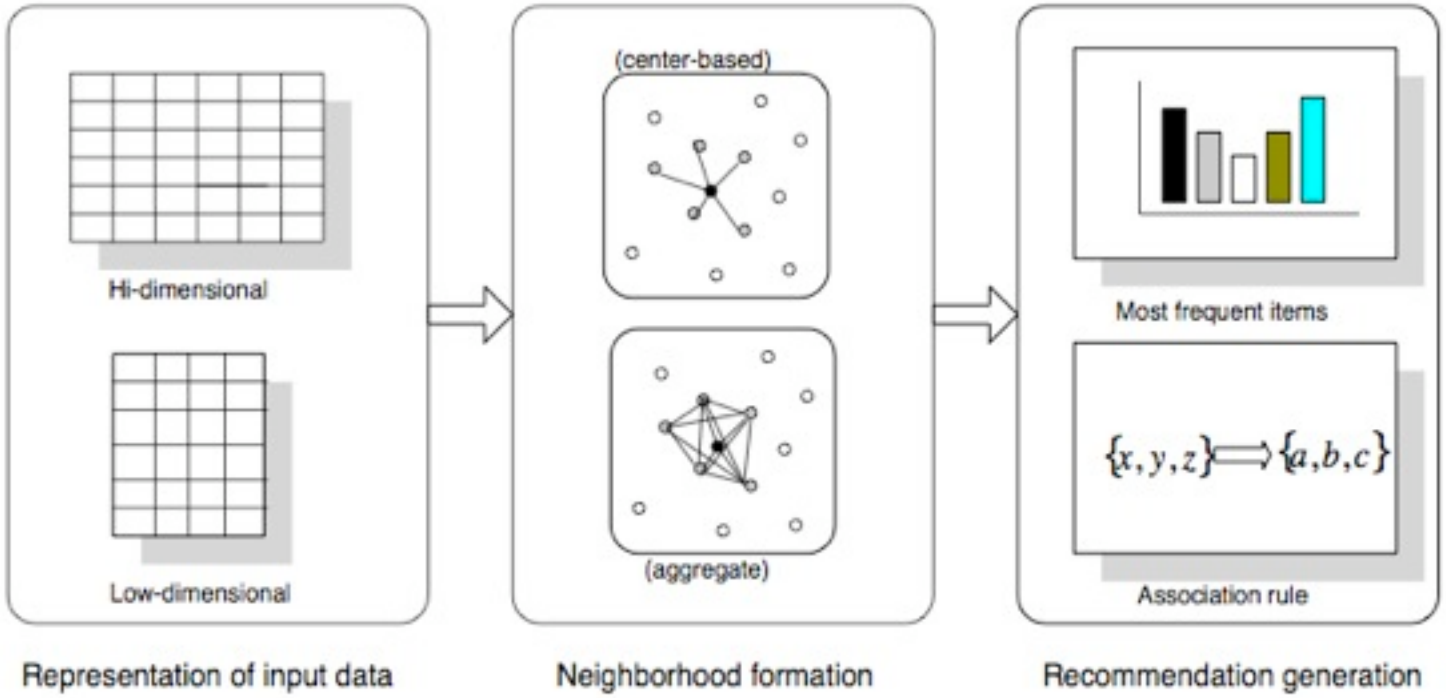


Figure 1: Three main parts of a Recommender System.

- Identify highly similar users to the active one
    - All with a measure greater than a threshold
    - Best K ones
- Prediction $r_{aj} = \bar{r}_a + \frac{\sum_i w(a,i)(r_{ij} - \bar{r}_i)}{\sum_i w(a,i)}$

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., IWAIS ’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.

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

$$U = \begin{bmatrix} 1.55 & 1.22 & 0.37 & 0.81 & 0.62 & -0.01 \\ 0.36 & 0.91 & 1.21 & 0.39 & 1.10 & 0.25 \\ 0.59 & 0.20 & 0.14 & 0.83 & 0.27 & 1.51 \\ 0.39 & 1.33 & -0.43 & 0.70 & -0.90 & 0.68 \\ 1.05 & 0.11 & 0.17 & 1.18 & 1.81 & 0.40 \end{bmatrix} \quad V = \begin{bmatrix} 1.00 & -0.05 & -0.24 & 0.26 & 1.28 & 0.54 & -0.31 & 0.52 \\ 0.19 & -0.86 & -0.72 & 0.05 & 0.68 & 0.02 & -0.61 & 0.70 \\ 0.49 & 0.09 & -0.05 & -0.62 & 0.12 & 0.08 & 0.02 & 1.60 \\ -0.40 & 0.70 & 0.27 & -0.27 & 0.99 & 0.44 & 0.39 & 0.74 \\ 1.49 & -1.00 & 0.06 & 0.05 & 0.23 & 0.01 & -0.36 & 0.80 \end{bmatrix}$$

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

$$\begin{pmatrix} u_{11} & \cdots & u_{1k} \\ \vdots & \ddots & \vdots \\ u_{m1} & \cdots & u_{mk} \end{pmatrix} \begin{pmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{k1} & \cdots & v_{kn} \end{pmatrix}$$

User-specific latent feature vector

Item-specific latent feature column vector

Matrix Factorization

- Optimization Problem
  - Given a *m x 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

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

Regularization terms

where $\lambda_1, \lambda_2 > 0$.

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

Social Recommendation Using Probabilistic Matrix Factorization

[Ma et al., CIKM2008]

Challenges

- Data sparsity problem

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

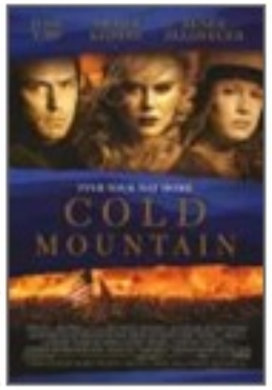
Yahoo! Users: B+ 137394 ratings
The Critics: A- 14 reviews

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

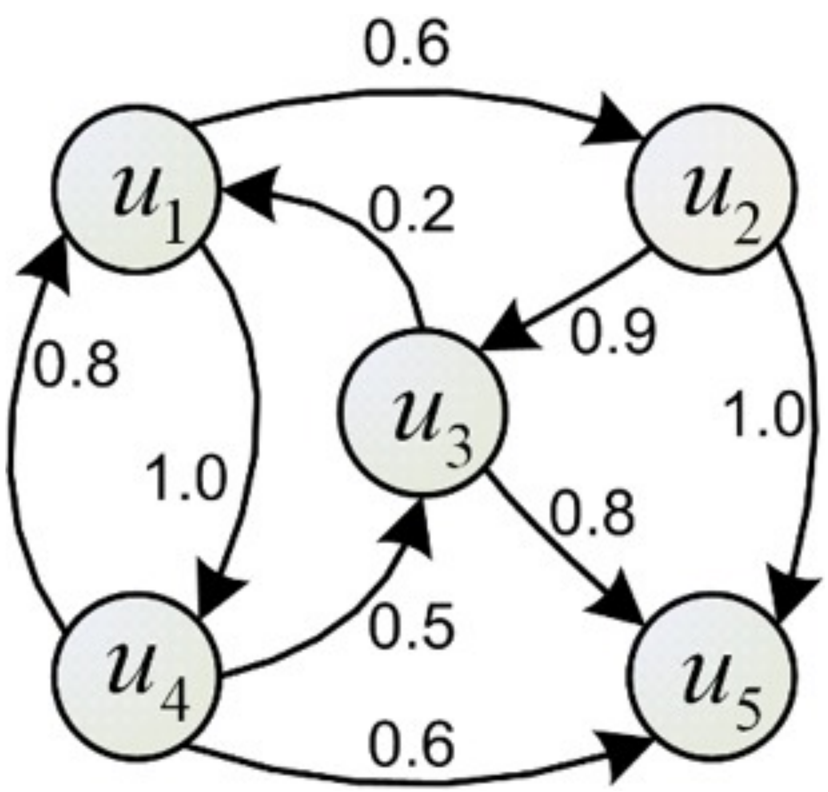
My Rating: B

Challenges

- Traditional recommender systems ignore the social connections between users

Recommendations from friends

Problem Definition



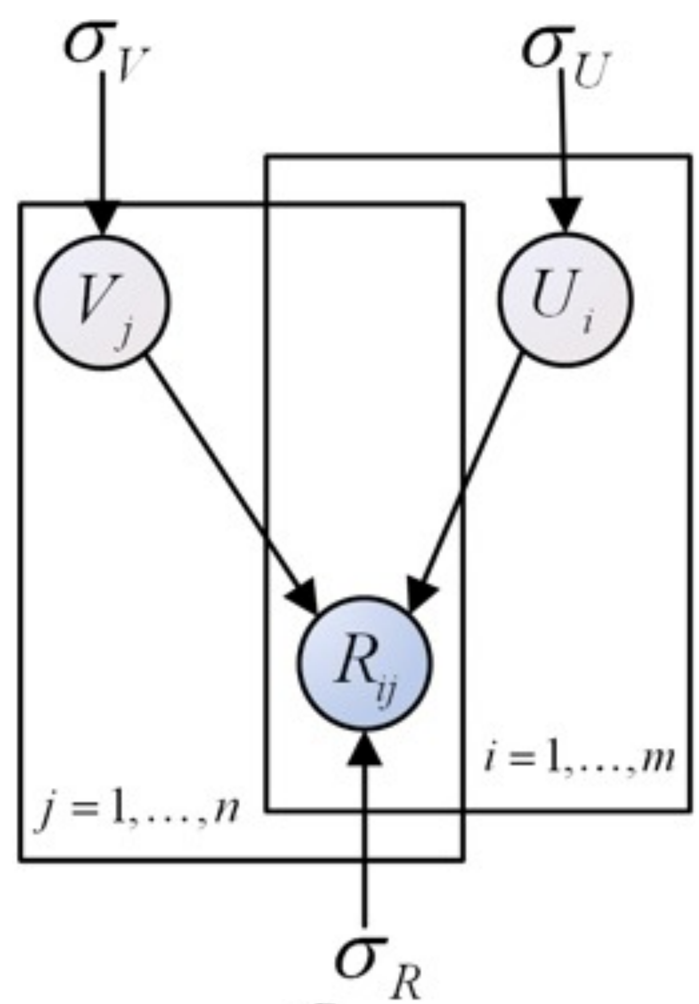
Social Trust Graph

	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



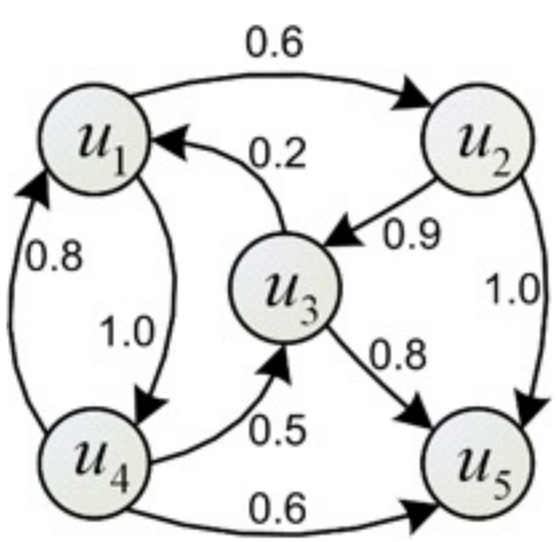
$$p(R|U, V, \sigma_R^2) = \prod_{i=1}^{m} \prod_{j=1}^{n} \left[\mathcal{N}\left(R_{ij} | g(U_i^T V_j), \sigma_R^2 \right) \right]^{I_{ij}^R}$$

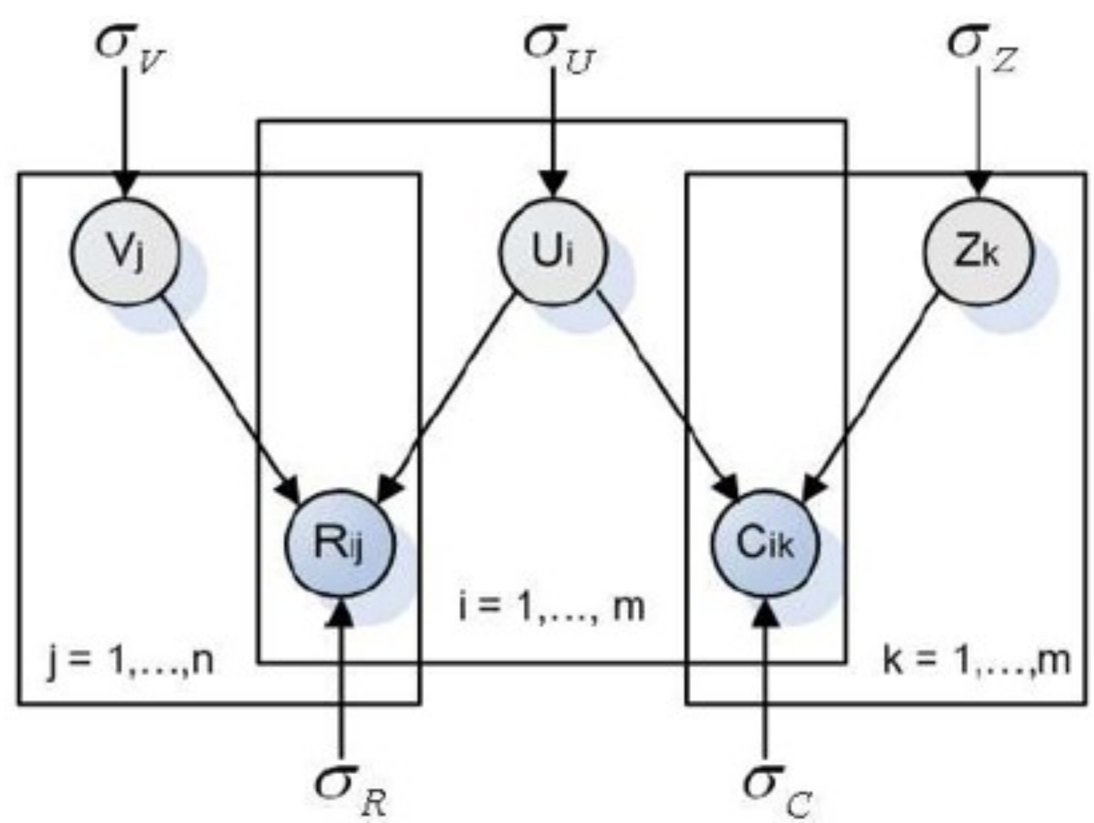
$$p(U|\sigma_U^2) = \prod_{i=1}^{m} \mathcal{N}(U_i | 0, \sigma_U^2 \mathbf{I}) \qquad p(V|\sigma_V^2) = \prod_{j=1}^{n} \mathcal{N}(V_j | 0, \sigma_V^2 \mathbf{I})$$

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

SoRec

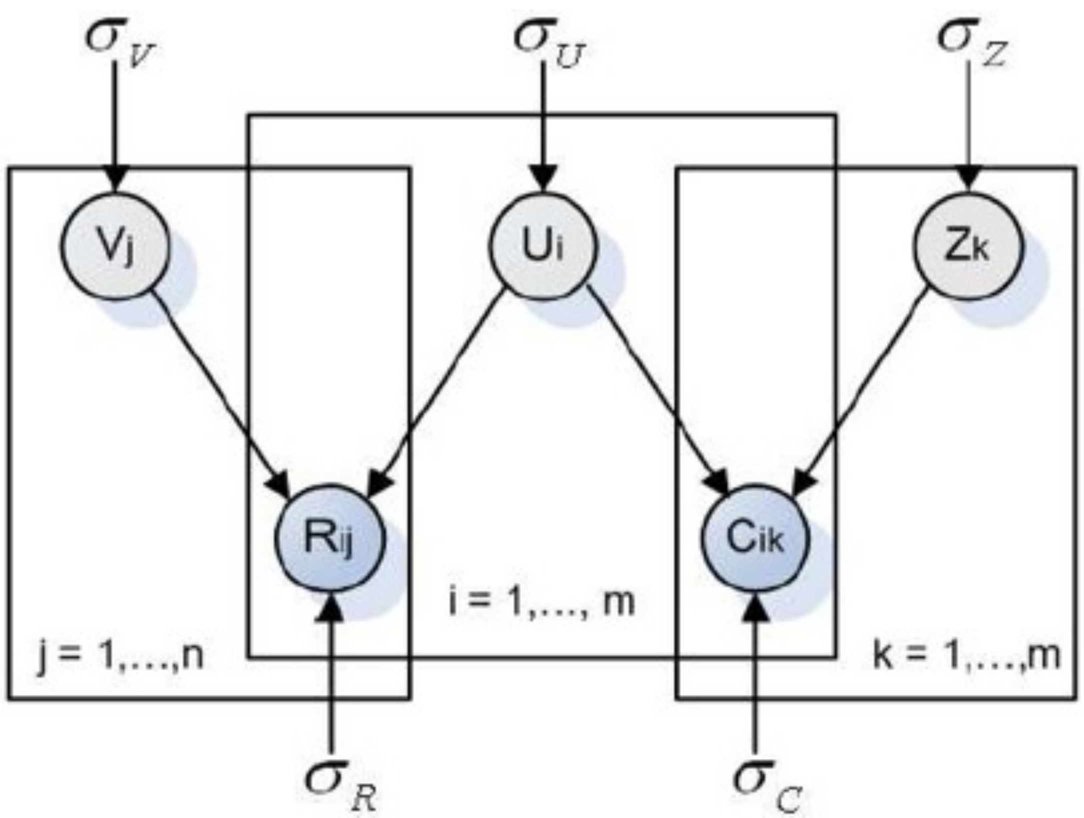
	v_1	v_2	v_3	v_4	v_5	v_6
u_1		5	2		3	
u_2	4			3		4
u_3			2			2
u_4	5			3		
u_5		5	5			3





SoRec

SoRec



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

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

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

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

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

SoRec

$$\frac{\partial \mathcal{L}}{\partial U_i} = \sum_{j=1}^{n} I_{ij}^R g'(U_i^T V_j)(g(U_i^T V_j) - r_{ij})V_j$$

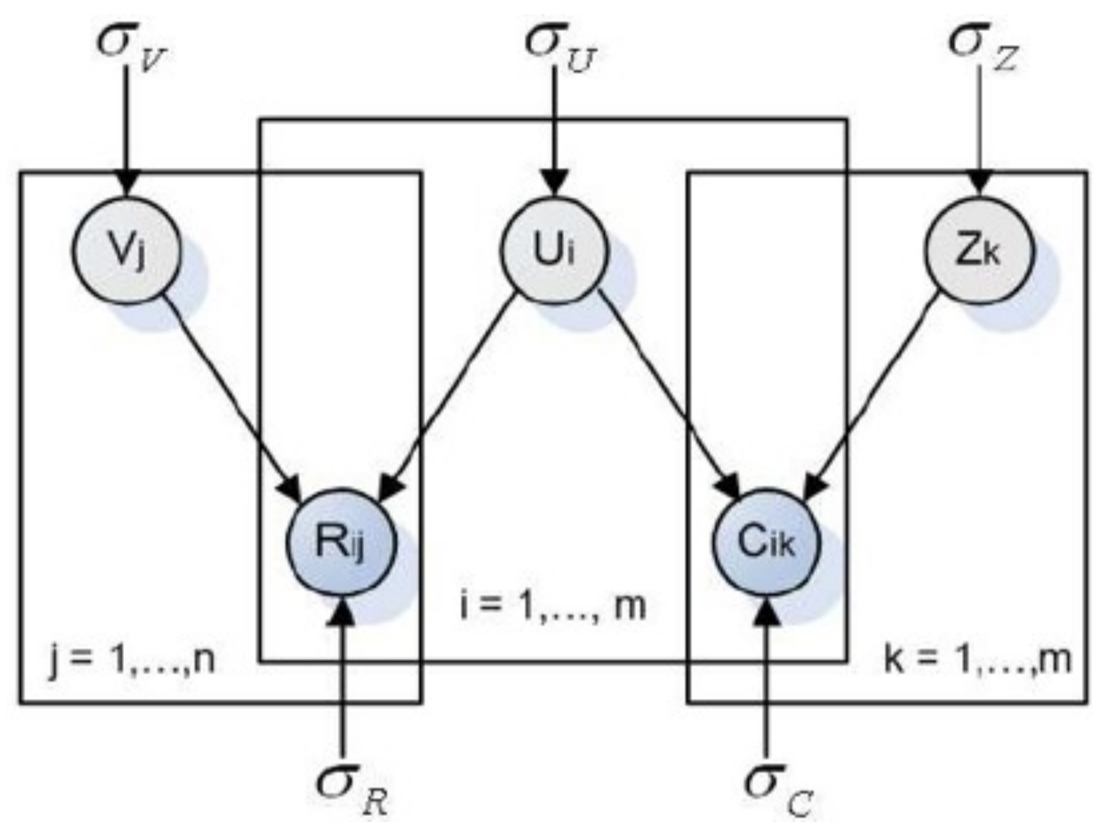
$$+ \lambda_C \sum_{j=1}^{m} I_{ik}^C g'(U_i^T Z_k)(g(U_i^T Z_k) - c_{ik}^*)Z_k + \lambda_U U_i,$$

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

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

Disadvantages of SoRec

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



SoRec

Learning to Recommend with Social Trust Ensemble

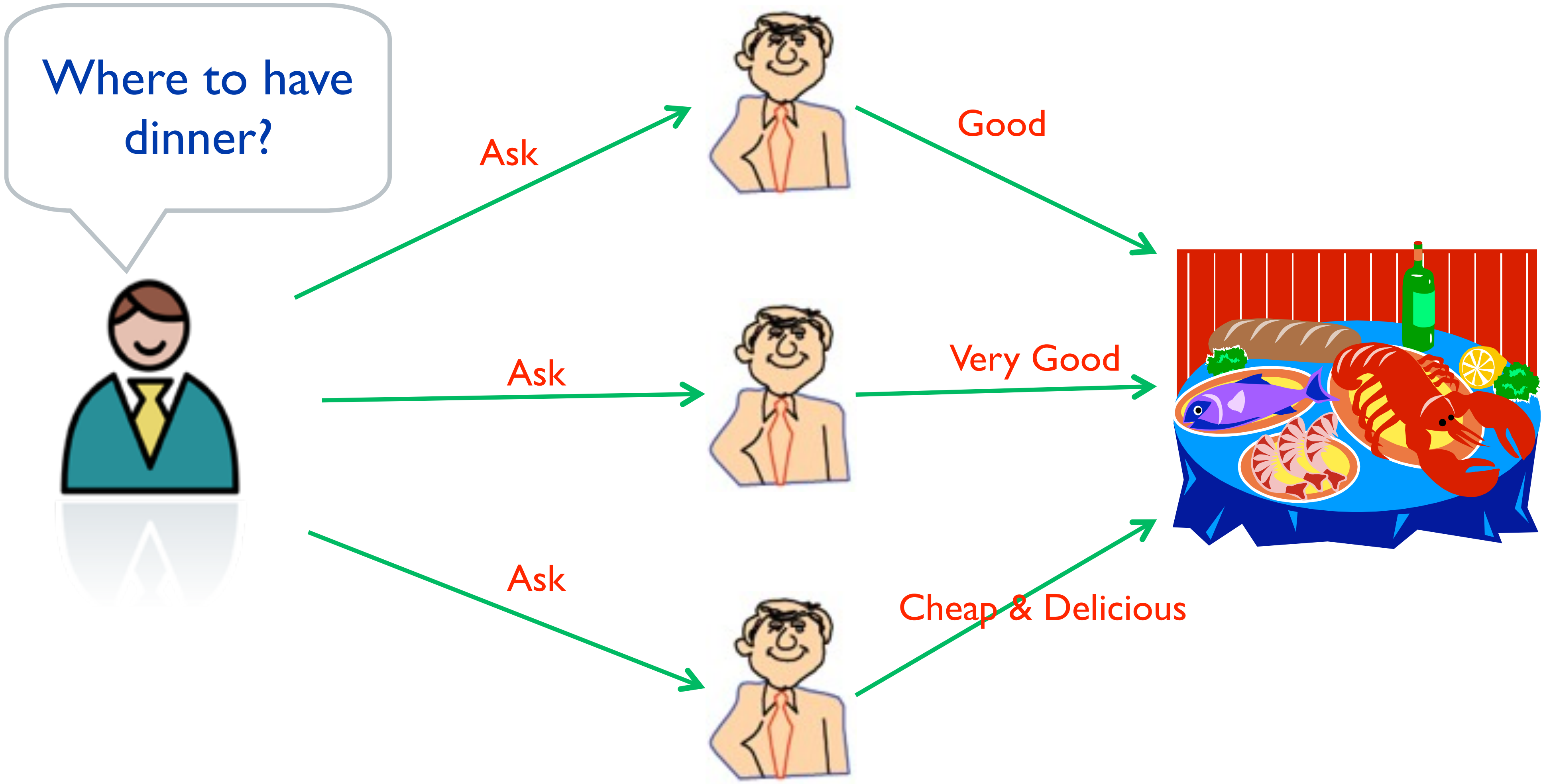
[Ma et al., SIGIR2009]

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

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



Motivations

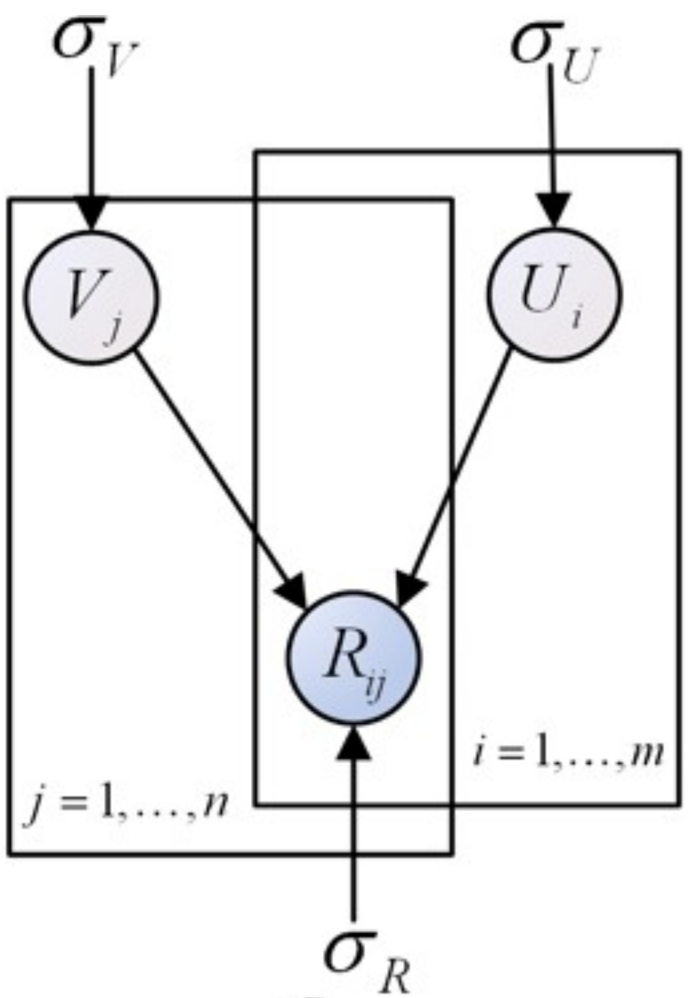
- Users have their own characteristics, and they have different tastes on different items, such as movies, books, music, articles, food, etc.

- 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]

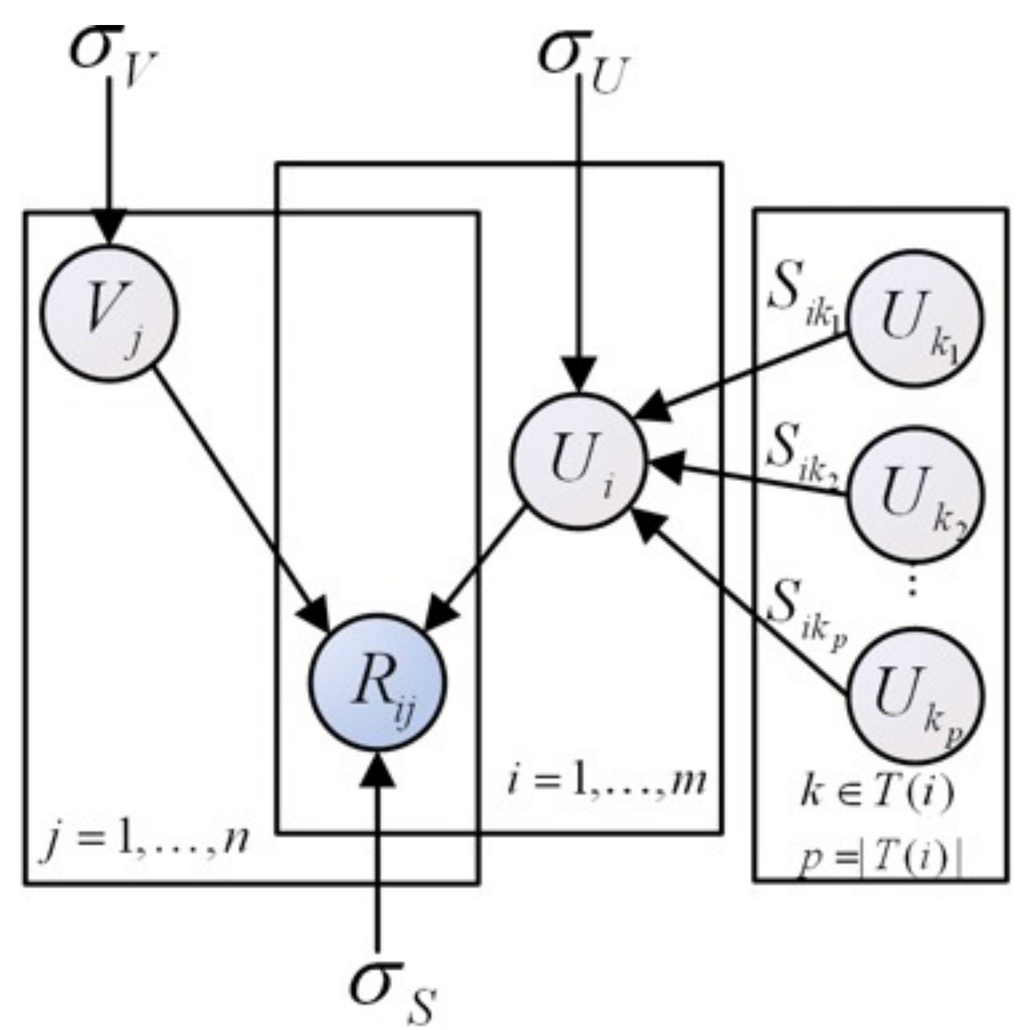
Recommendations by Trusted Friends

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

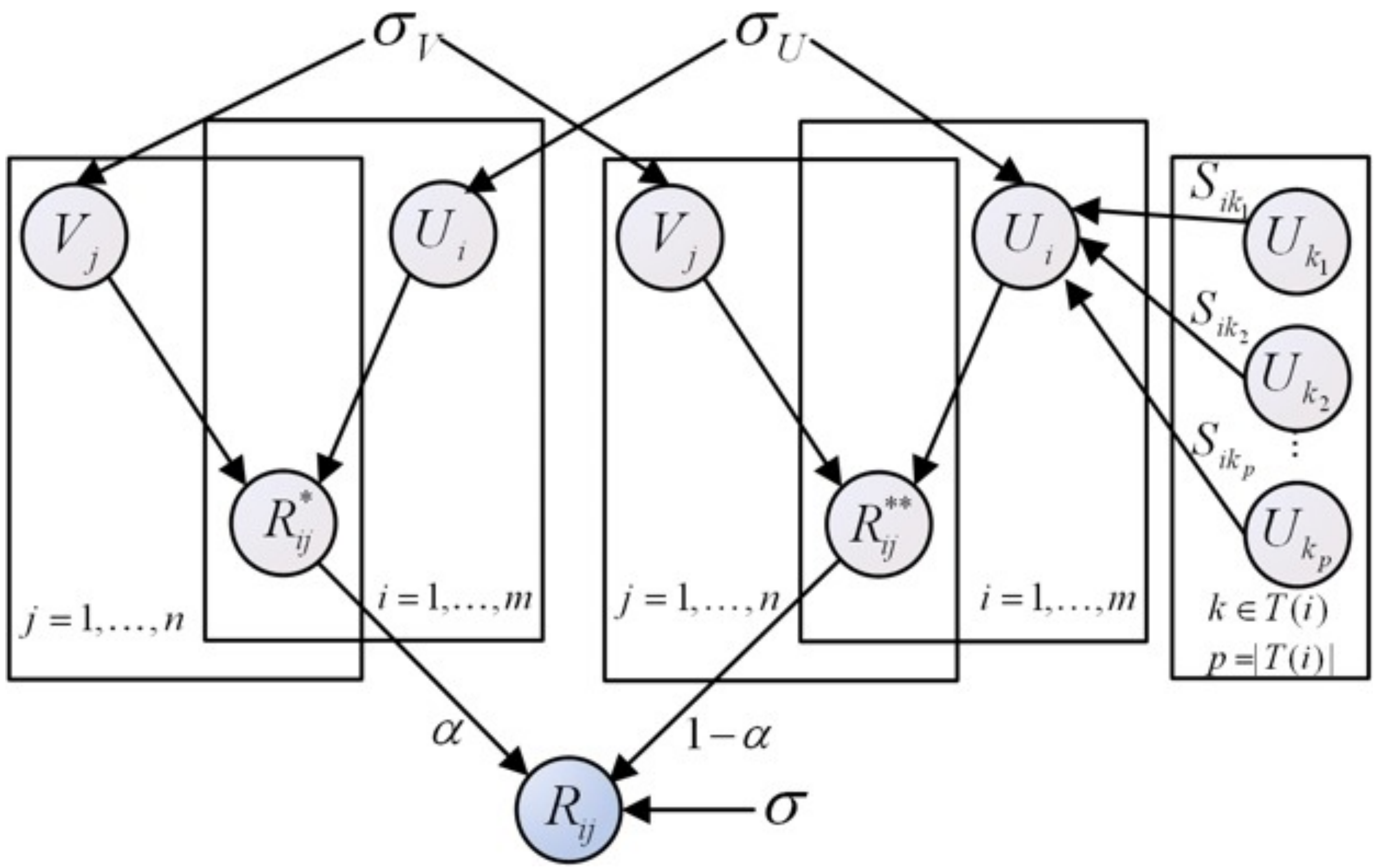
$$\widehat{R}_{ik} = \sum_{j \in \mathcal{T}(i)} R_{jk} S_{ij}$$

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

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



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

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

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

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

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
  - 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

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

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

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

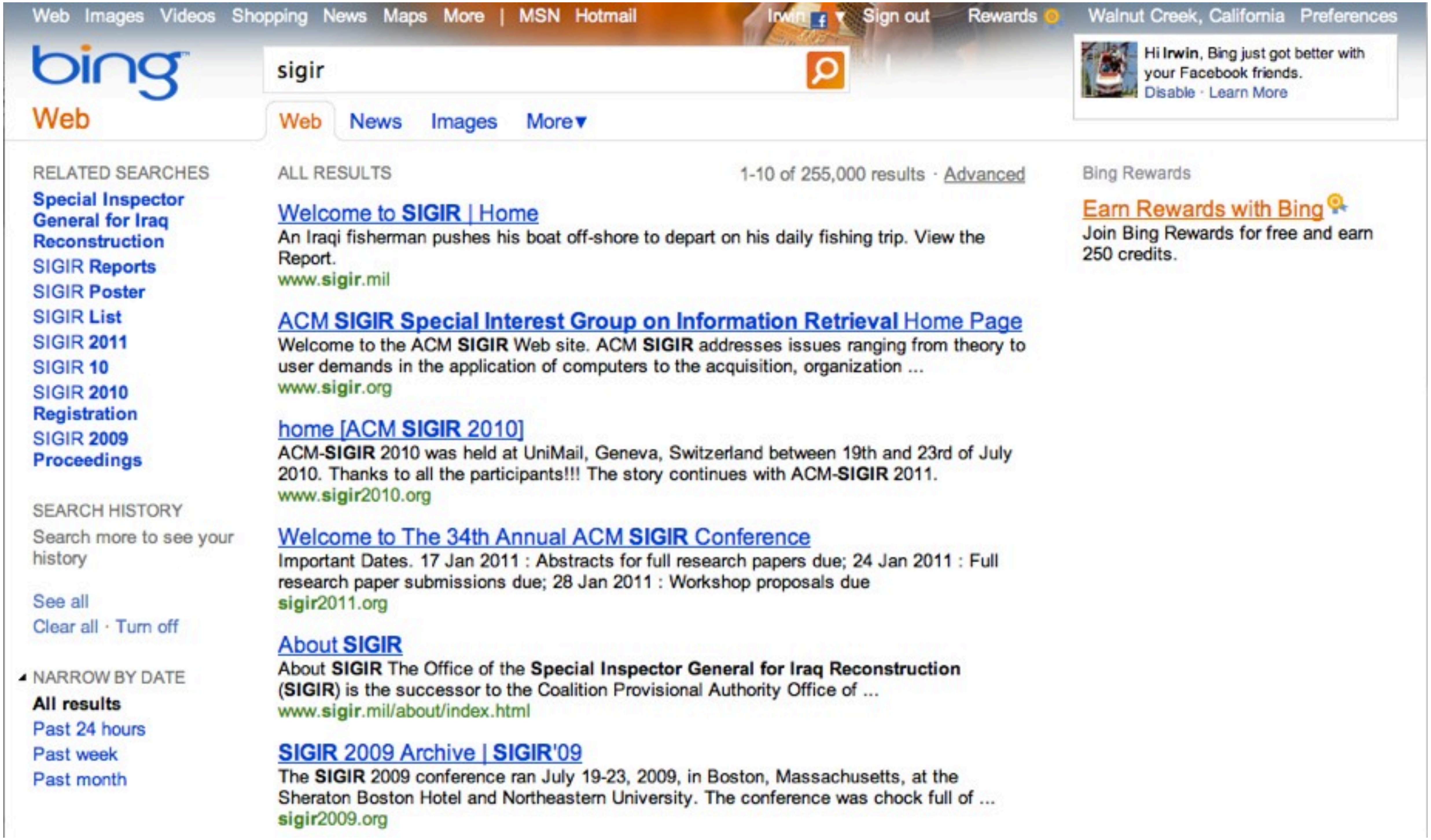
$$\min_{U} \frac{1}{2}\sum_{i=1}^{m}\sum_{t\in\mathcal{T}^{+}(i)} S_{it}^{\mathcal{T}}\|U_i - U_t\|_F^2$$

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

Web Site Recommendation

[Ma et al., SIGIR 2011]

Traditional Search Paradigm



“Search” to “Discovery”

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
...	...	...

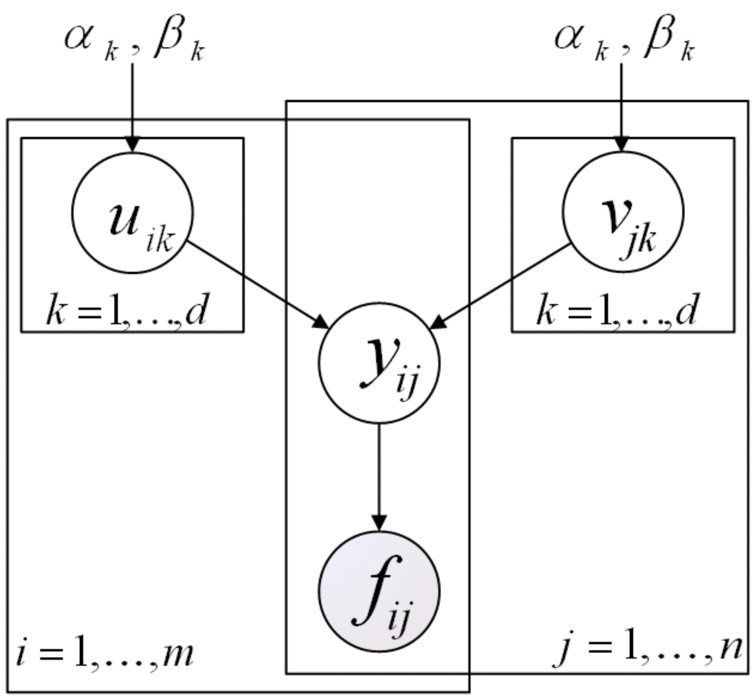
Web sites

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

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

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

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

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

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

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

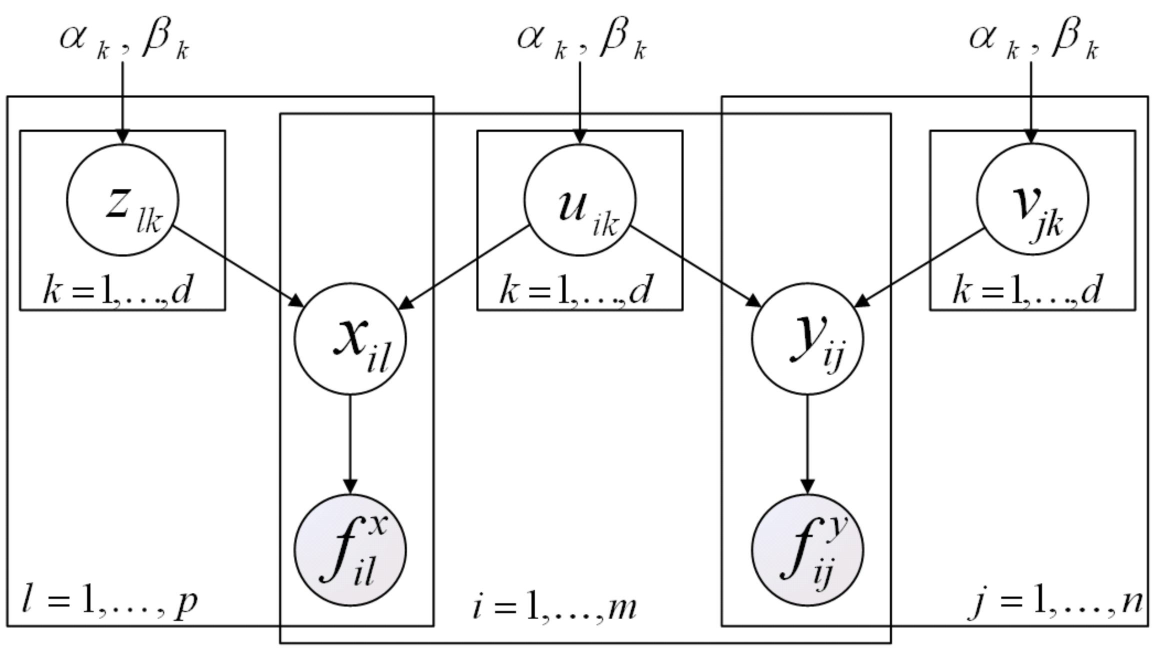
Probabilistic Factor Model

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

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

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

Collective Probabilistic Factor Model



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

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

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

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

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

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
- 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

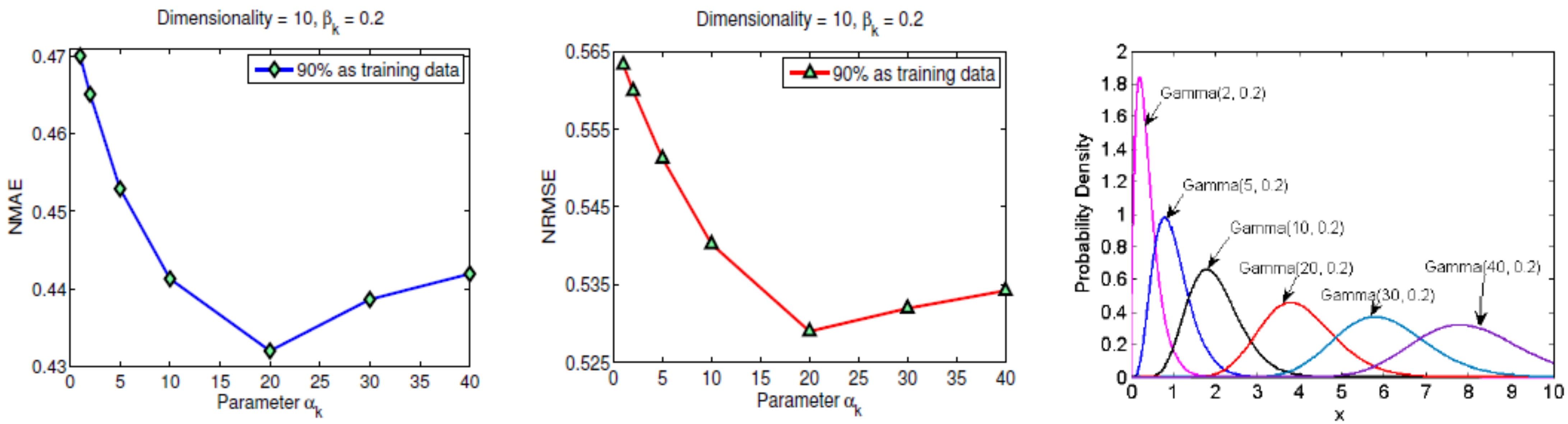
Table 3: Performance Comparison (Dimensionality = 10)

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)

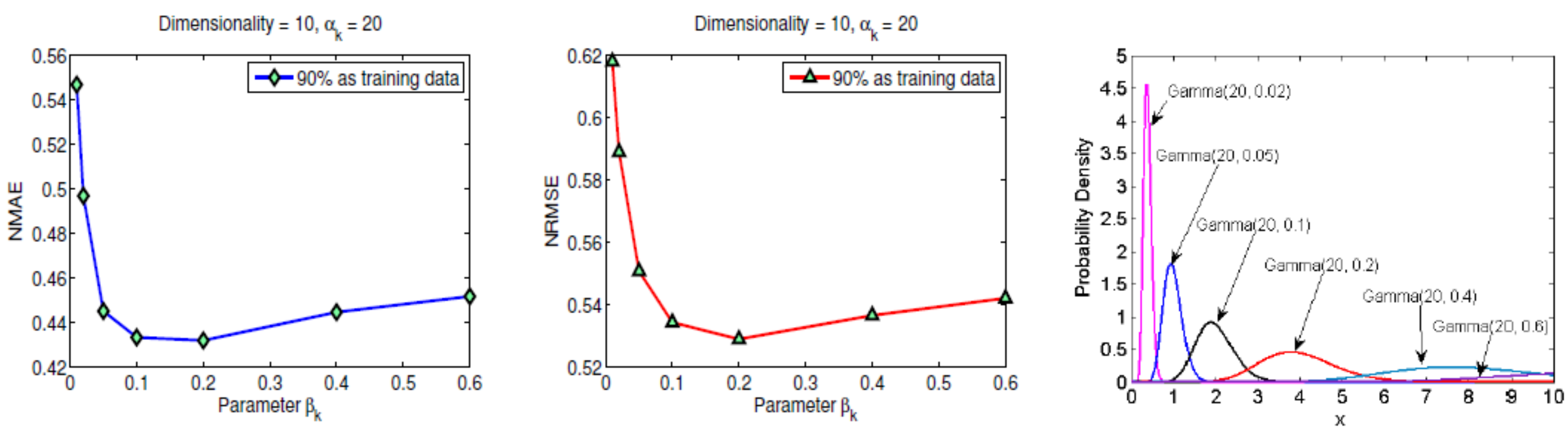
Training Data	Metrics	UserMean	SiteMean	SVD	PMF	NMF	GaP	PFM	CPFM
90%	NMAE	2.246	1.094	0.469	0.460	0.449	0.426	0.413	**0.409**
	Improve	81.79%	62.61%	12.79%	11.09%	8.91%	3.99%		
	NRMSE	3.522	2.171	0.568	0.556	0.542	0.521	0.503	**0.496**
	Improve	85.92%	77.15%	12.68%	10.79%	8.49%	4.80%		
80%	NMAE	2.252	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

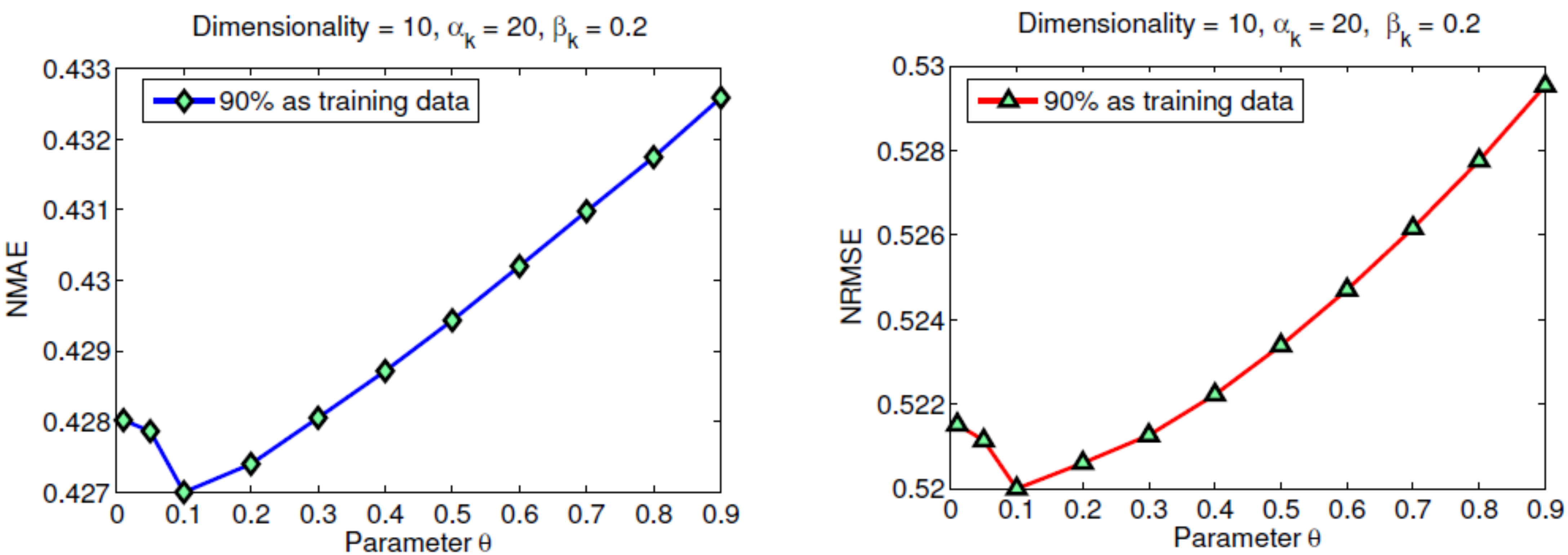
Figure 6: Impact of Parameter α_k in PFM



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

Figure 7: Impact of Parameter β_k in PFM

Impact of Parameters



(a) NMAE (b) NRMSE

Figure 8: Impact of Parameter θ 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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On-Going Research

Machine Learning

- Smooth Optimization for Effective Multiple Kernel Learning (AAAI'10)
- Simple and Efficient Multiple Kernel Learning By Group Lasso (ICML'10)
- Online Learning for Group Lasso (ICML'10)
- Heavy-Tailed Symmetric Stochastic Neighbor Embedding (NIPS'09)
- Adaptive Regularization for Transductive Support Vector Machine (NIPS'09)
- Direct Zero-norm Optimization for Feature Selection (ICDM'08)
- Semi-supervised Learning from General Unlabeled Data (ICDM'08)
- Learning with Consistency between Inductive Functions and Kernels (NIPS'08)
- An Extended Level Method for Efficient Multiple Kernel Learning (NIPS'08)
- Semi-supervised Text Categorization by Active Search (CIKM'08)
- Transductive Support Vector Machine (NIPS'07)
- Global and local learning (ICML'04, JMLR'04)

On-Going Research

Web Intelligence/Information Retrieval

- Learning to Suggest Questions in Online Forums (AAAI'11)
- Diversifying Query Suggestion Results (AAAI'10)
- A Generalized Co-HITS Algorithm and Its Application to Bipartite Graphs (KDD'09)
- Entropy-biased Models for Query Representation on the Click Graph (SIGIR'09)
- Effective Latent Space Graph-based Re-ranking Model with Global Consistency (WSDM'09)
- Formal Models for Expert Finding on DBLP Bibliography Data (ICDM'08)
- Learning Latent Semantic Relations from Query Logs for Query Suggestion (CIKM'08)
- RATE: a Review of Reviewers in a Manuscript Review Process (WI'08)
- MatchSim: link-based web page similarity measurements (WI'07)
- Diffusion rank: Ranking web pages based on heat diffusion equations (SIGIR'07)
- Web text classification (WWW'07)

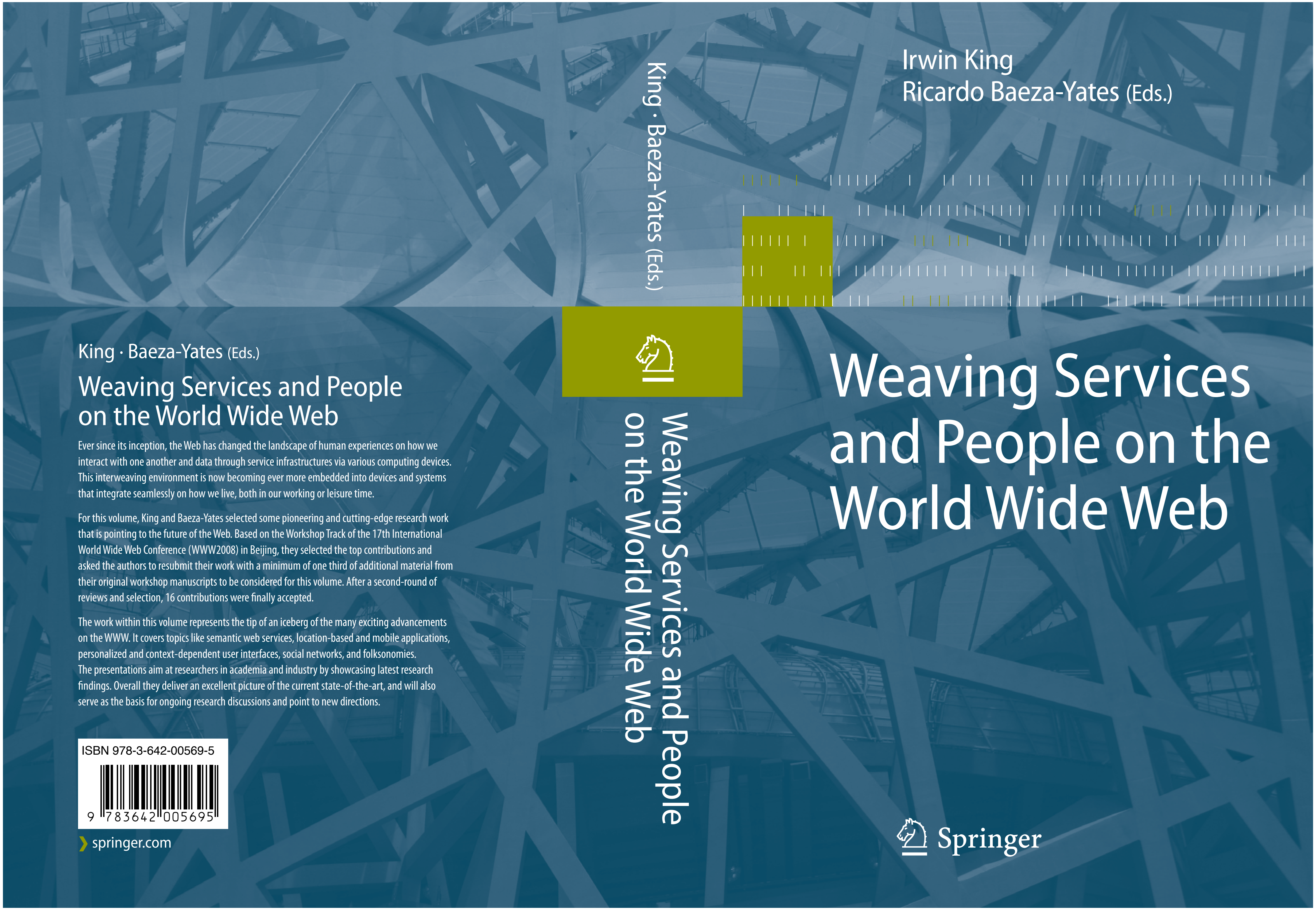
On-Going Research

Recommender Systems/Collaborative Filtering

- Probabilistic Factor Models for Web Site Recommendation (SIGIR'11)
- Recommender Systems with Social Regularization (WSDM'11)
- UserRec: A User Recommendation Framework in Social Tagging Systems (AAAI'10)
- Learning to Recommend with Social Trust Ensemble (SIRIR'09)
- Semi-Nonnegative Matrix Factorization with Global Statistical Consistency in Collaborative Filtering (CIKM'09)
- Recommender system: accurate recommendation based on sparse matrix (SIGIR'07)
- SoRec: Social Recommendation Using Probabilistic Matrix Factorization (CIKM'08)

Human Computation

- A Survey of Human Computation Systems (SCA'09)
- Mathematical Modeling of Social Games (SIAG'09)
- An Analytical Study of Puzzle Selection Strategies for the ESP Game (WI'08)
- An Analytical Approach to Optimizing The Utility of ESP Games (WI'08)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Ever since its inception, the Web has changed the landscape of human experiences on how we interact with one another and data through service infrastructures via various computing devices. This interweaving environment is now becoming ever more embedded into devices and systems that integrate seamlessly on how we live, both in our working or leisure time.
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The work within this volume represents the tip of an iceberg of the many exciting advancements on the WWW. It covers topics like semantic web services, location-based and mobile applications, personalized and context-dependent user interfaces, social networks, and folksonomies.
The presentations aim at researchers in academia and industry by showcasing latest research findings. Overall they deliver an excellent picture of the current state-of-the-art, and will also serve as the basis for ongoing research discussions and point to new directions.
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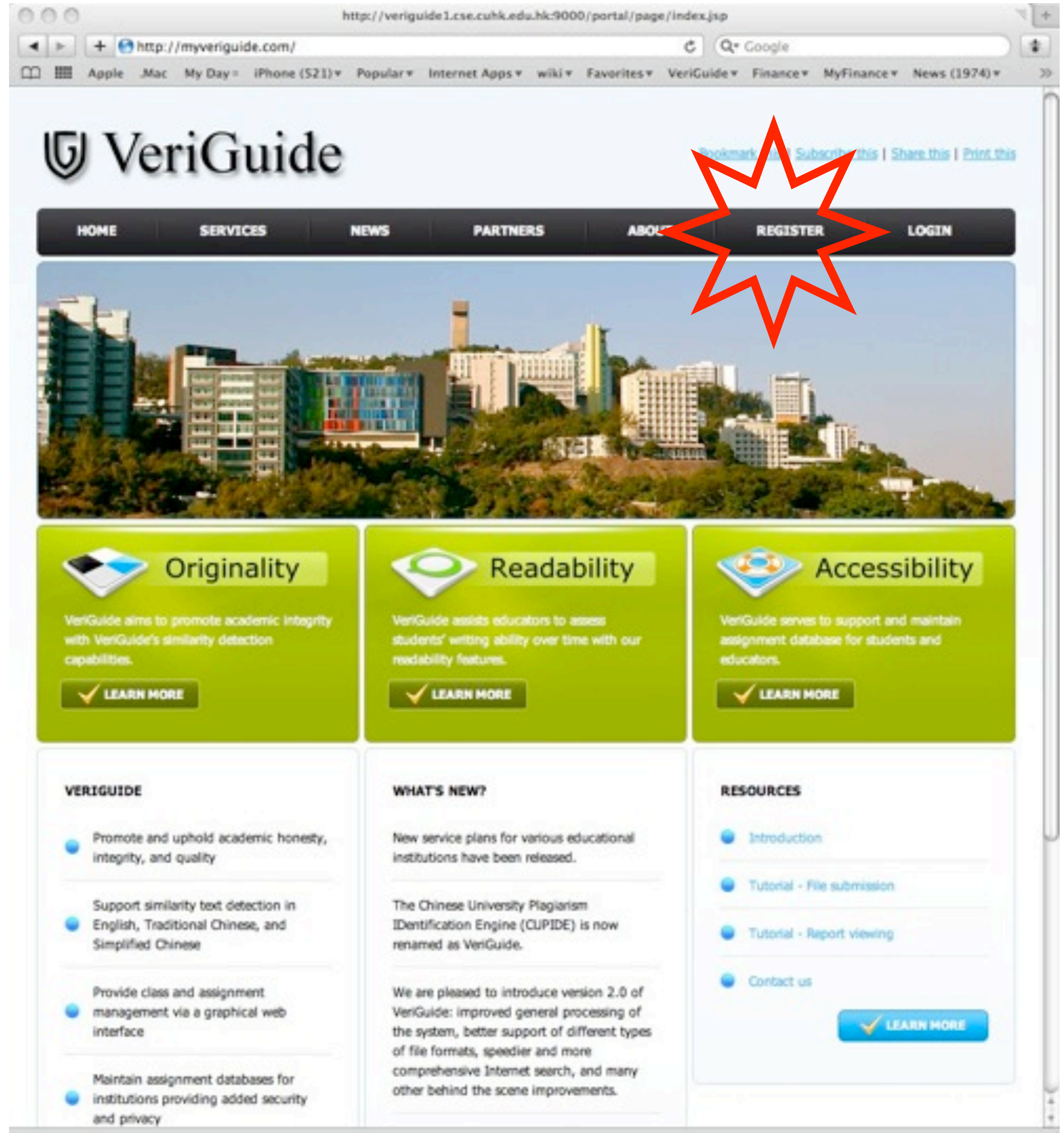

Q & A