

Recent Developments in Social and Location Recommendations

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Joint work with Hao Ma and Cheng Chen

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The Chinese University of Hong Kong

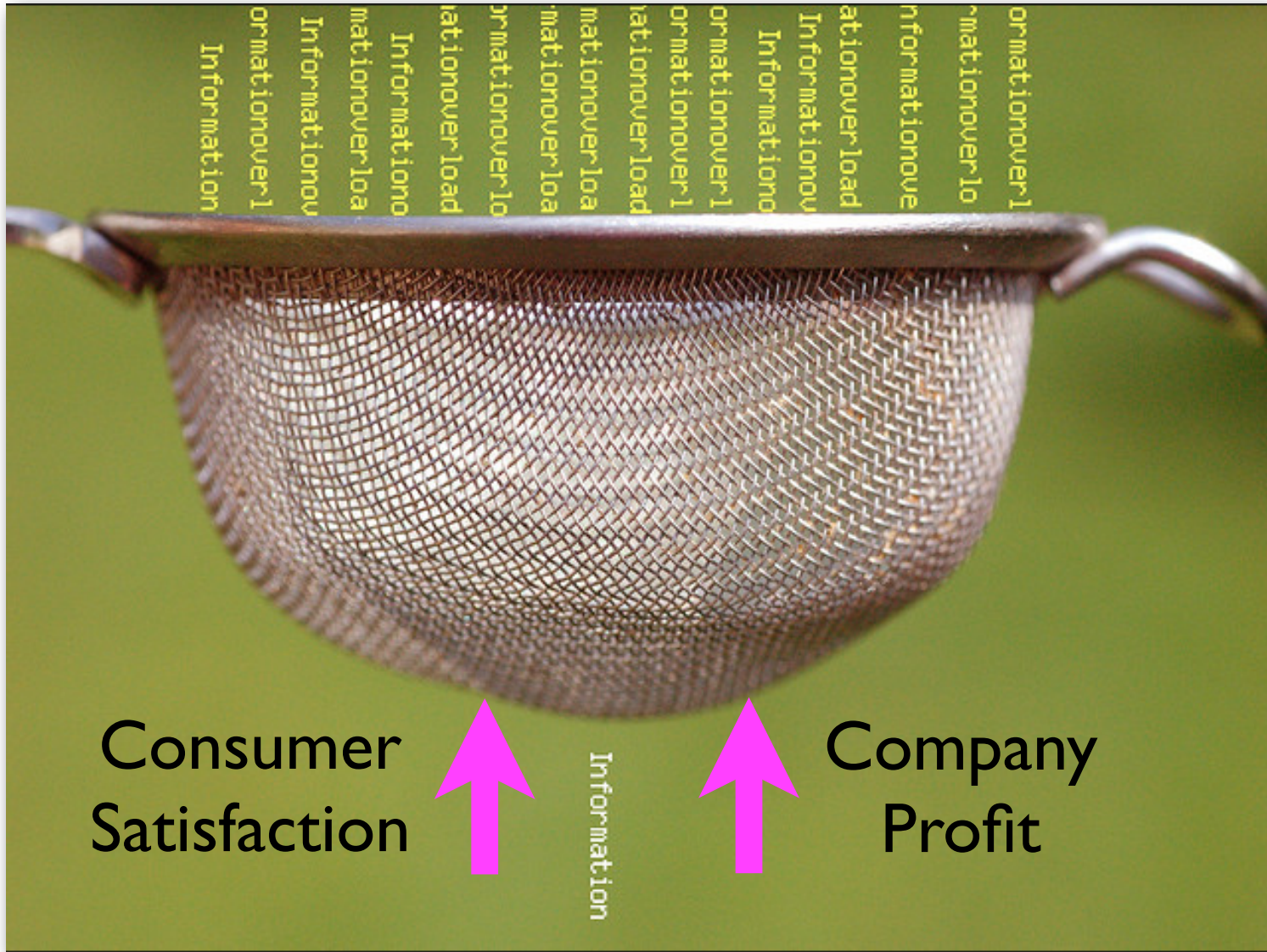
king@cse.cuhk.edu.hk
<http://www.cse.cuhk.edu.hk/~king>

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Information and more Information!





Consumer
Satisfaction

Information

Company
Profit

Recent Developments in Social and Location Recommendations, Irwin King
Jeju Island, South Korea August 8, 2012



Real Life Examples

The screenshot shows the Amazon.com interface for a book. At the top, there's a navigation bar with the Amazon logo, a search bar containing 'Books', and various utility links like 'Cart' and 'Wish List'. Below the navigation bar, the product title 'Weaving Services and People on the World Wide Web [Hardcover]' is displayed, along with the editors' names: Irwin King and Ricardo Baeza-Yates. The price is shown as \$79.11, with a 'FREE with Super Saver Shipping' offer. A 'LOOK INSIDE!' button is visible on the book cover image. To the right of the product details, there are buttons for 'Add to Cart' and 'Add to Cart with FREE Two-Day Shipping'. Below the product details, there's a section for 'More Buying Choices' showing 31 used & new items for \$14.62. At the bottom of the product page, there's a red oval highlighting the text 'Customers Who Bought This Item Also Bought'.

amazon.com Hello. [Sign in](#) to get personalized recommendations. New customer? [Start here](#). **FREE 2-Day Shipping: See details**

Your Amazon.com | [Today's Deals](#) | [Gifts & Wish Lists](#) | [Gift Cards](#) | Your Digital Items | Your Account | Help

Shop All Departments Search Books GO Cart Wish List

Books Advanced Search Browse Subjects New Releases Bestsellers The New York Times® Bestsellers Libros en español Bargain Books Textbooks

Click to **LOOK INSIDE!**

Weaving Services and People on the World Wide Web [Hardcover]
Irwin King (Editor), Ricardo Baeza-Yates (Editor)
[Be the first to review this item](#) | Like (0)

List Price: ~~\$99.00~~
Price: **\$79.11** & this item ships for **FREE with Super Saver Shipping**. [Details](#)
You Save: **\$19.89 (20%)**

In Stock.
Ships from and sold by Amazon.com. Gift-wrap available.
Only 2 left in stock--order soon (more on the way).

Want it delivered Thursday, July 21? Order it in the next **0 hours and 19 minutes**, and choose **One-Day Shipping** at checkout. [Details](#)

18 new from \$14.62 **13 used** from \$14.62

Quantity: 1

Add to Cart
or
[Sign in](#) to turn on 1-Click ordering.
or
Add to Cart with FREE Two-Day Shipping
Amazon Prime Free Trial required. Sign up when you check out. [Learn More](#)

Add to Wish List

More Buying Choices
31 used & new from \$14.62
Have one to sell? [Sell yours here](#)

Share your own customer images
[Search inside this book](#)

FREE Two-Day Shipping for Students. [Learn more](#)

Share

Customers Who Bought This Item Also Bought



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Real Life Examples

amazon.com | Hao's Amazon.com | See All 40 Product Categories | Your Account |  Cart | Your Lists  | Help | 


Your Browsing History | Recommended For You | Rate These Items | Improve Your Recommendations | Your Profile | Learn More

Today's Recommendations For You

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



[Amar Es Combatir](#)  ~ Maná
★★★★☆ (55) \$8.49



Real Life Examples

YAHOO! MOVIES

My Movies: gabe_ma [Edit Profile](#)

Recommendations For You

[Receive Recommendations by Email](#)

Movies in Theaters: 94089



Burn After Reading (R)

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

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

The Critics: **B** 14 reviews

Don't Recommend Again Seen It? Rate It!



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)

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

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](#)



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!



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]



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 top 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.



Social Recommendation Using Probabilistic Matrix Factorization

[Ma et al., CIKM2008]



Challenges

- Data sparsity problem

YAHOO! MOVIES

My Movies: **gabe_ma** [Edit Profile](#)

Recommendations For You



[Watch the Trailer](#)

My Blueberry Nights (2008)

The Critics:

B-

[7 reviews](#)

Yahoo! Users:

B-

[667 ratings](#)

My Grade:

A+

Oscar-worthy

[write a review](#)

A

B

C

D

F



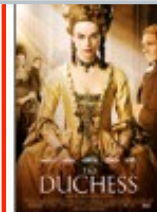
Vicky Cristina Barcelona (PG-13)

[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](#)

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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

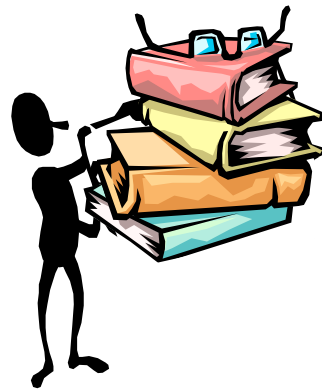
The Critics: **B** 15 reviews

★ My Rating: B



Challenges

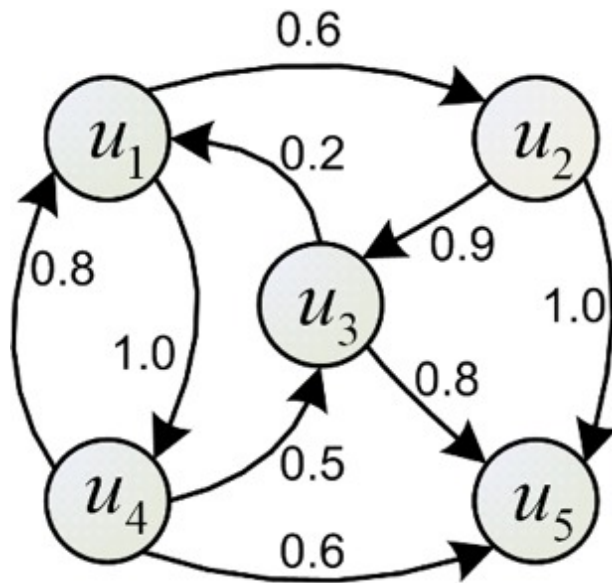
- Traditional recommender systems ignore the social connections between users



Recommendations
from friends



Problem Definition



Social Trust Graph

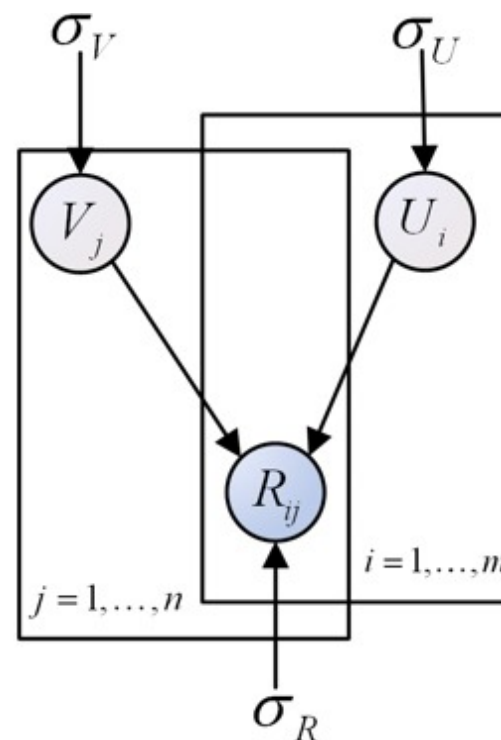
	v_1	v_2	v_3	v_4	v_5	v_6
u_1		5	2		3	
u_2	4			3		4
u_3			2			2
u_4	5			3		
u_5		5	5			3

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



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

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

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

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

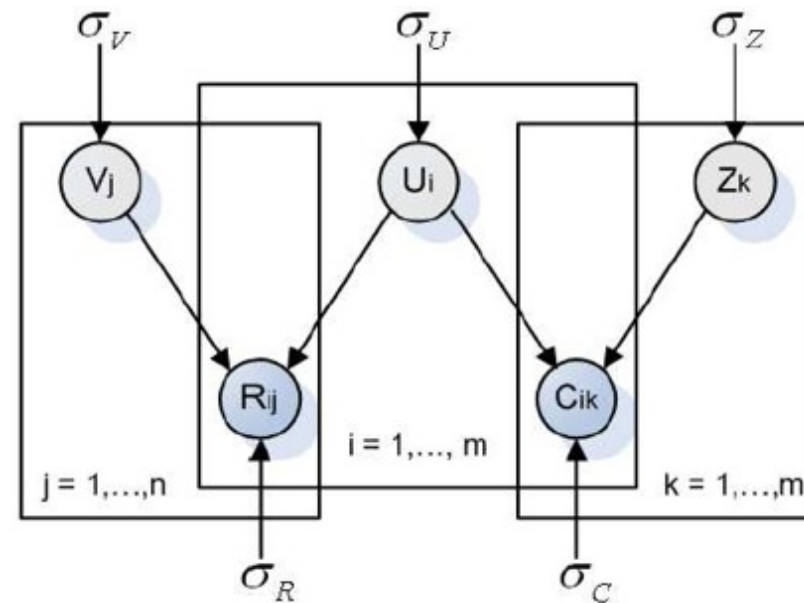
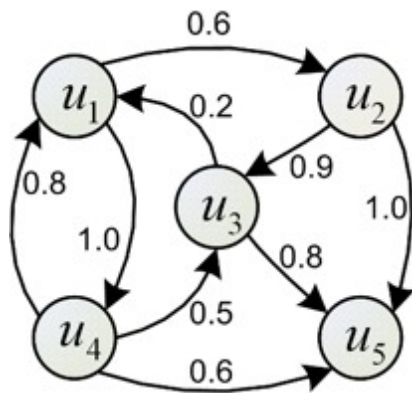
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Jeju Island, South Korea

August 8, 2012



SoRec

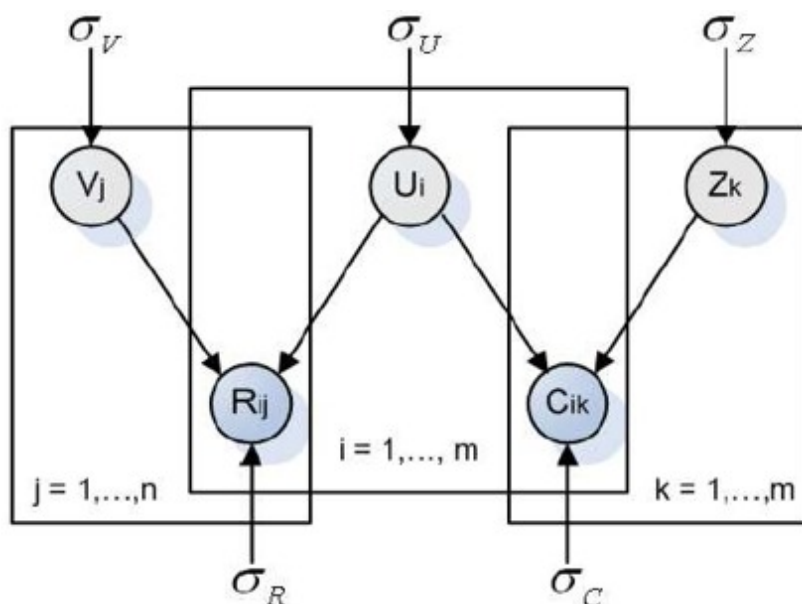
	v_1	v_2	v_3	v_4	v_5	v_6
u_1		5	2		3	
u_2	4			3		4
u_3			2			2
u_4	5			3		
u_5		5	5			3



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

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

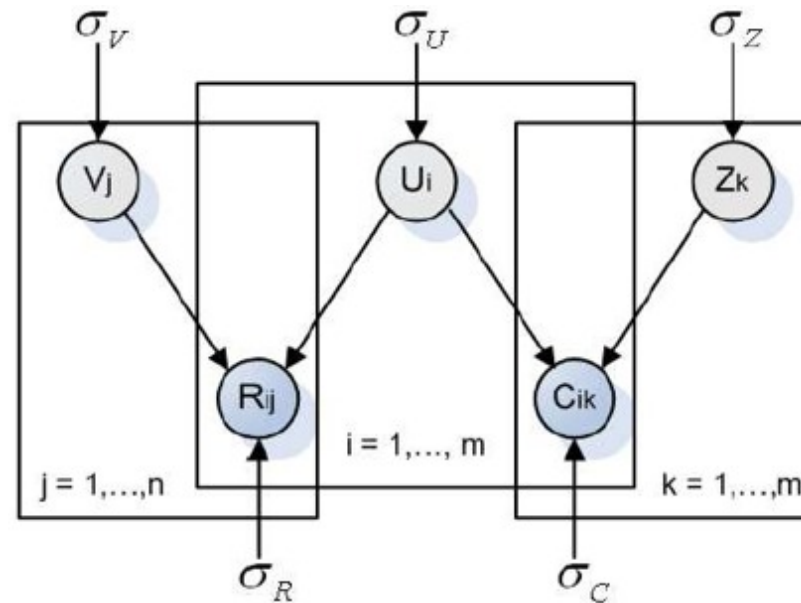
$$\frac{\partial \mathcal{L}}{\partial V_j} = \sum_{i=1}^m I_{ij}^R g'(U_i^T V_j) (g(U_i^T V_j) - r_{ij}) U_i + \lambda_V V_j,$$

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



Disadvantages of SoRec

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



SoRec



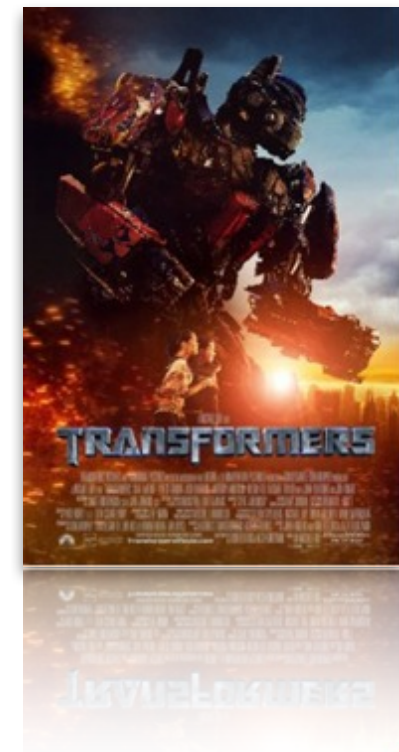
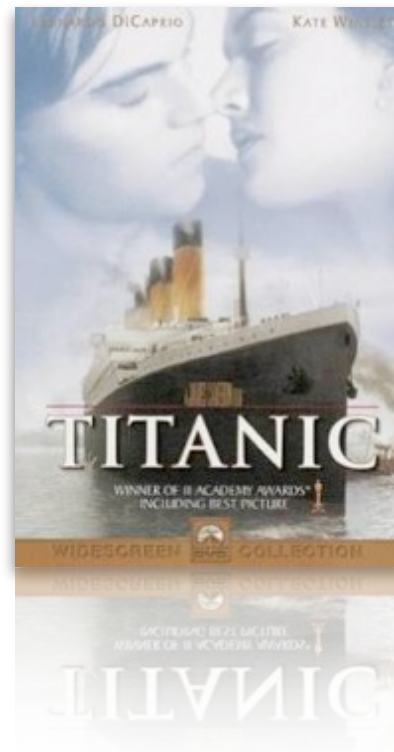
Learning to Recommend with Social Trust Ensemble

[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.

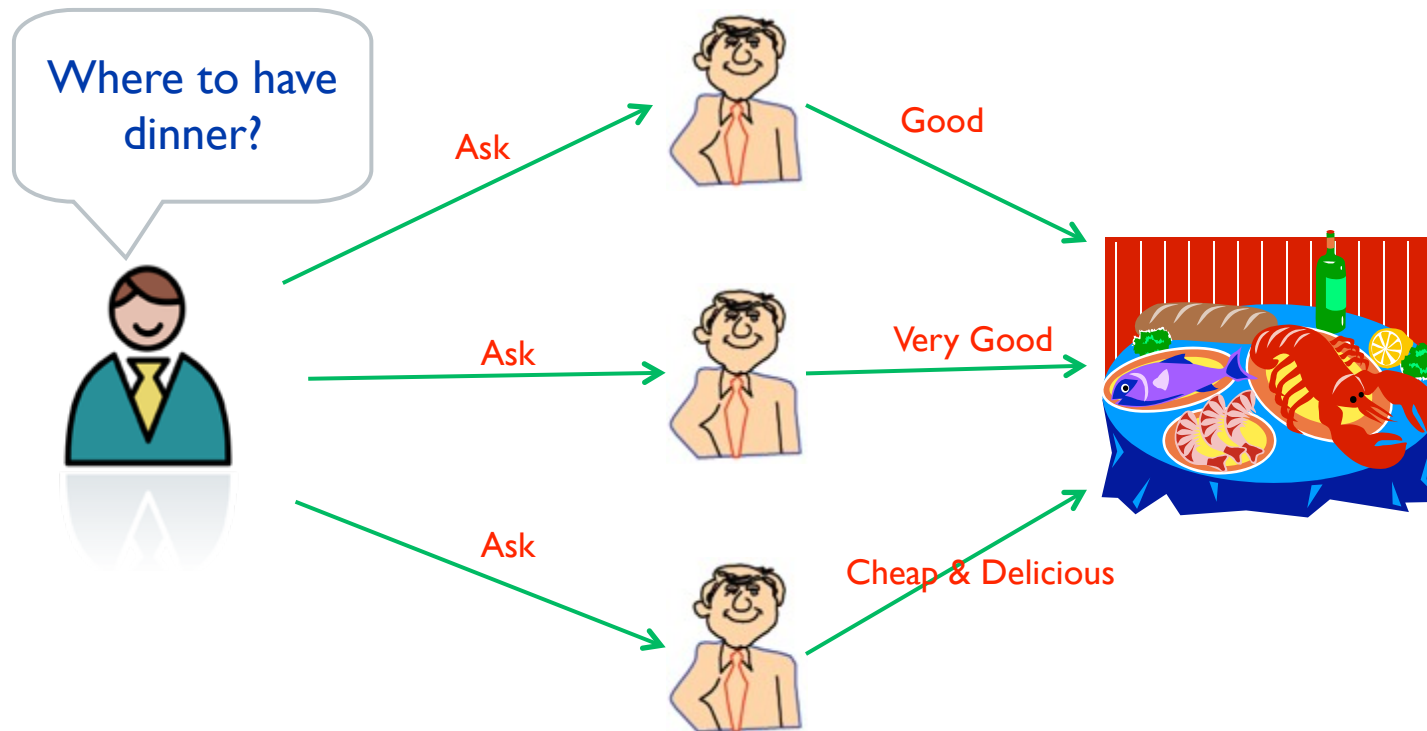


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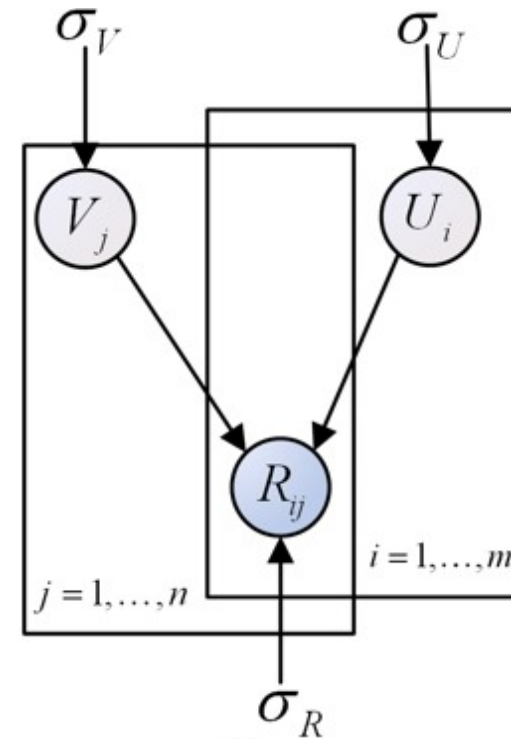
2nd Motivation

- 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]

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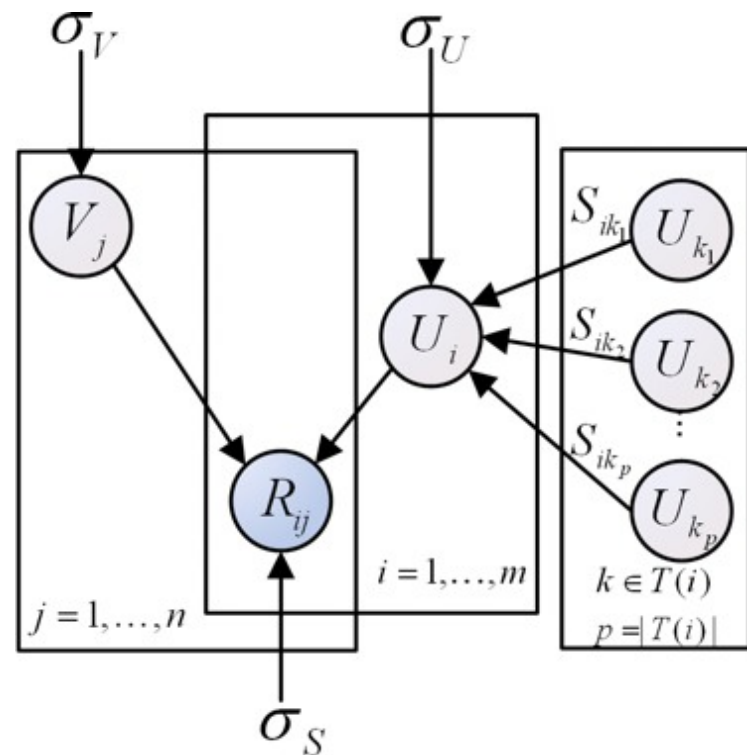
Recommendations by Trusted Friends

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

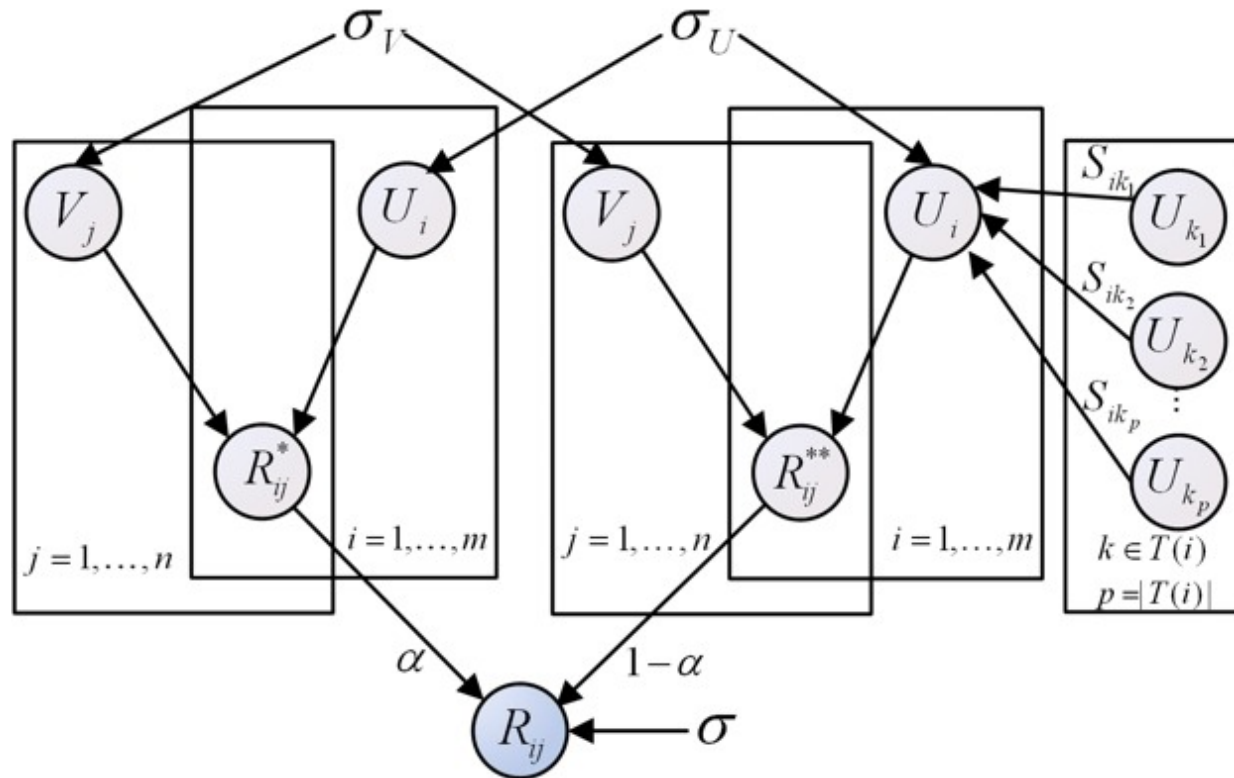
$$\hat{R}_{ik} = \sum_{j \in \mathcal{T}(i)} R_{jk} S_{ij}$$

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

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



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

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

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

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



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 options like "Irwin", "Sign out", and "Rewards". The location is set to "Walnut Creek, California". The search bar contains "sigir" and shows "1-10 of 255,000 results".

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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

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

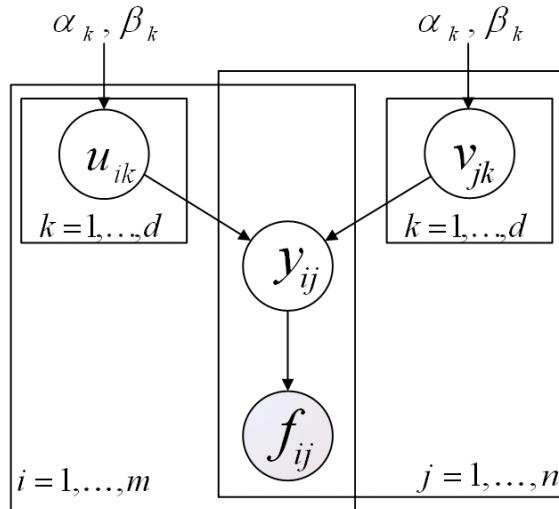
$$p(R|U, V, \sigma_R^2) = \prod_{i=1}^m \prod_{j=1}^n \left[\mathcal{N}(R_{ij} | U_i V_j^T, \sigma_R^2) \right]^{I_{ij}}$$

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

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



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

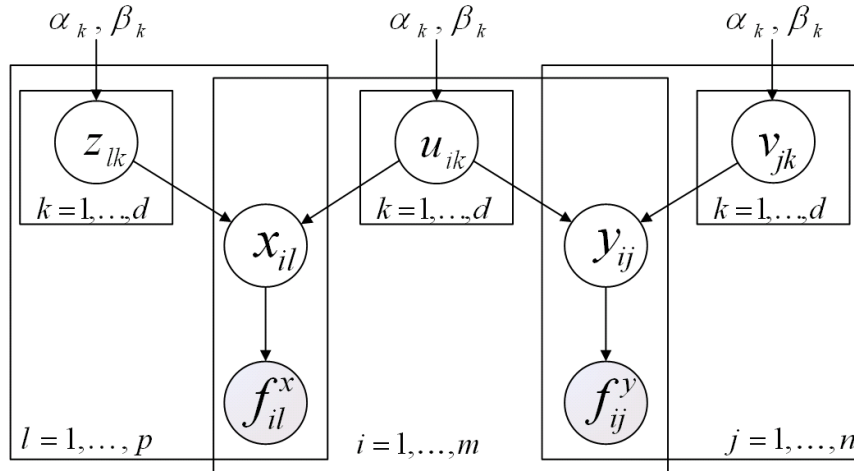
$$\begin{aligned}\mathcal{L}(U, V; F) &= \sum_{i=1}^m \sum_{k=1}^d ((\alpha_k - 1) \ln(u_{ik}/\beta_k) - u_{ik}/\beta_k) \\ &\quad + \sum_{j=1}^n \sum_{k=1}^d ((\alpha_k - 1) \ln(v_{jk}/\beta_k) - v_{jk}/\beta_k) \\ &\quad + \sum_{i=1}^m \sum_{j=1}^n (f_{ij} \ln y_{ij} - y_{ij}) + \text{const.}\end{aligned}$$

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

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



Collective Probabilistic Factor Model



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

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

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

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

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

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



Location Recommendations

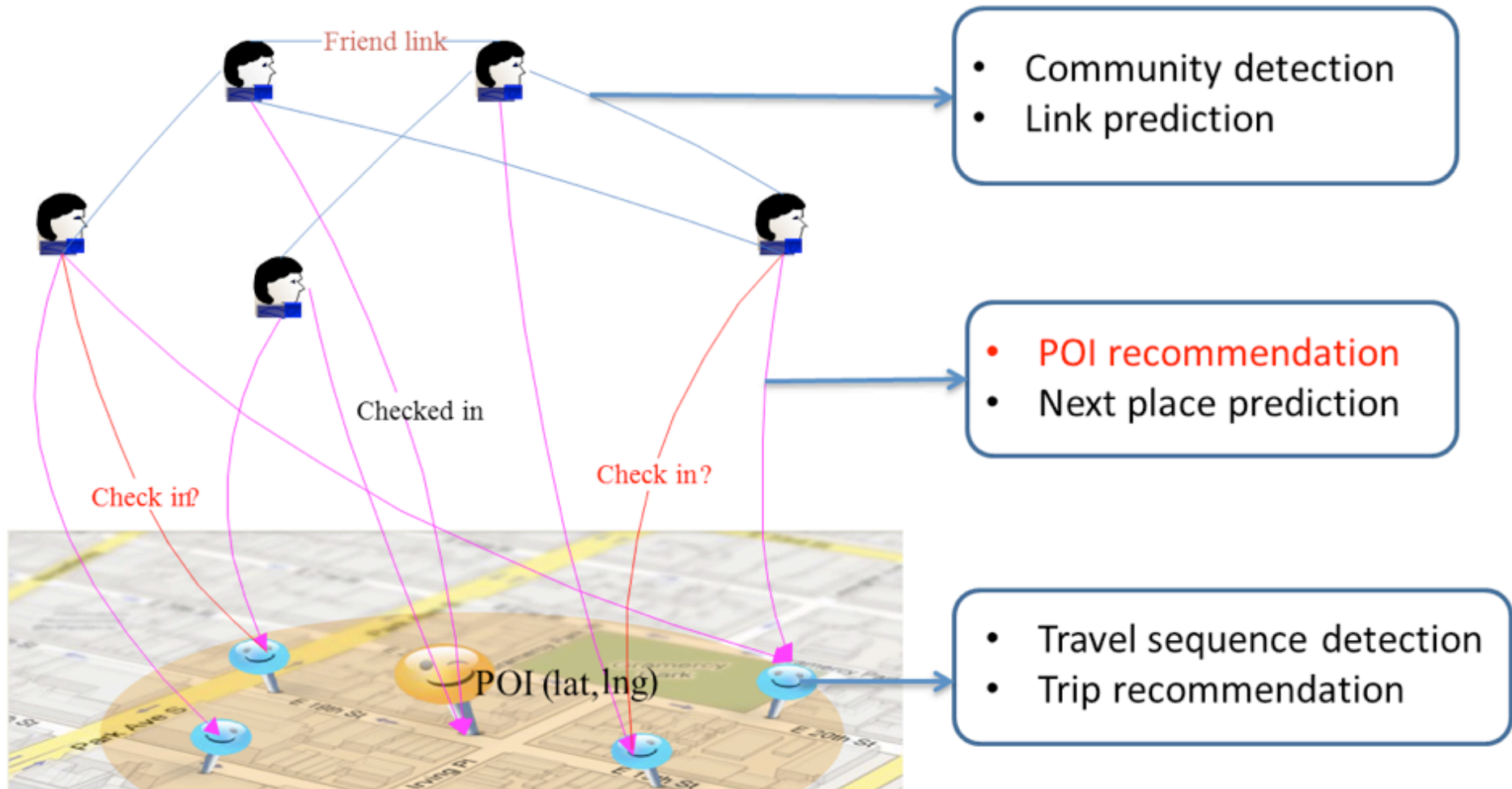
[Cheng et al., AAAI 2012]



Check Out on “Check-ins”



Location-based Social Networks (LBSNs)



Motivations

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



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

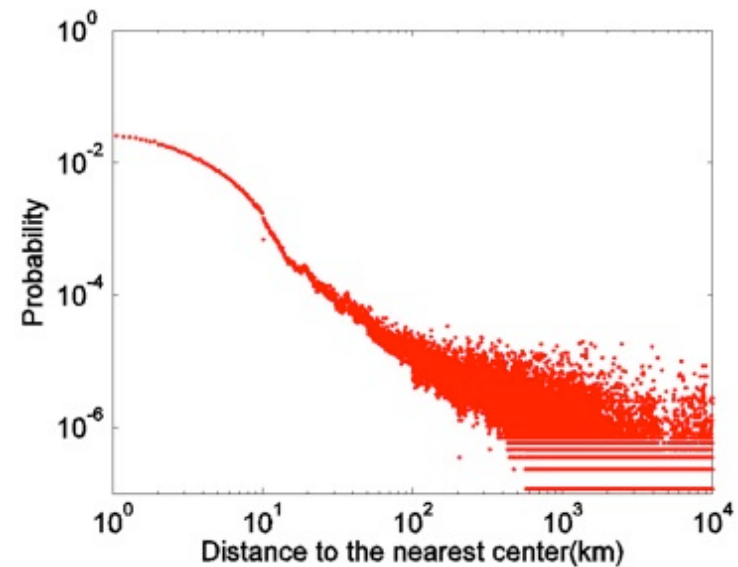
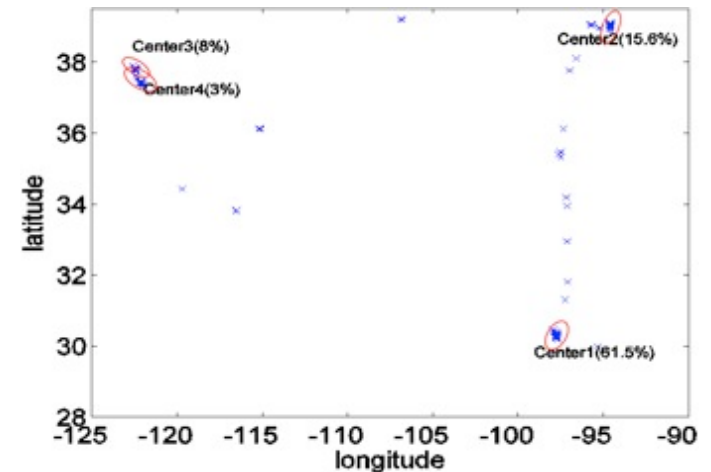


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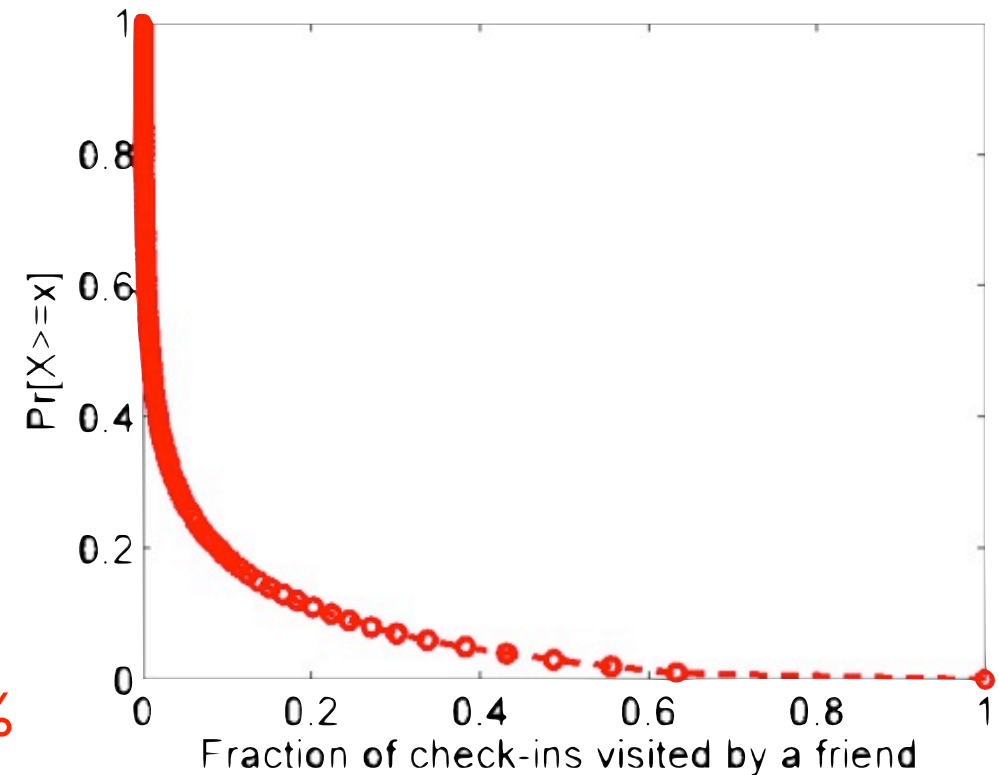
Observation #1

- 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

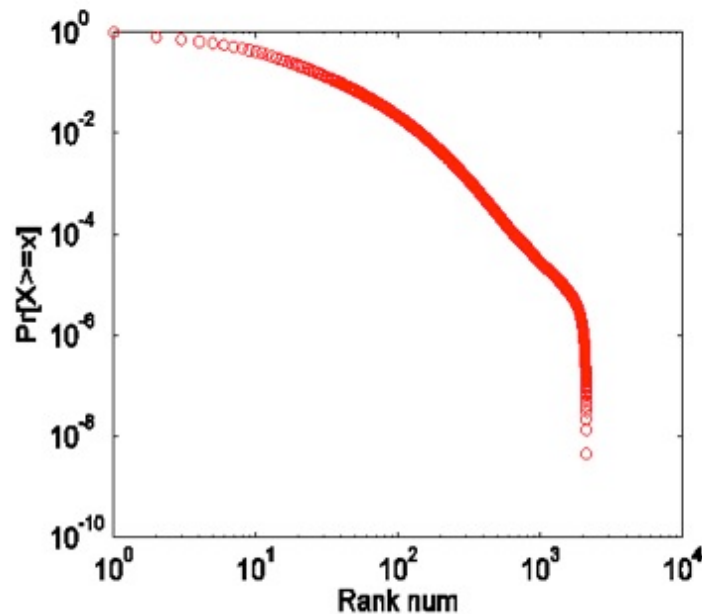
- Notations
 - C_u : multi-center set for user u
 - f_{c_u} : total frequency at center c_u for user u
 - $\mathcal{N}(l|\mu_{c_u}, \Sigma_{c_u})$: the pdf of Gaussian distribution, μ_{c_u} and Σ_{c_u} denote the mean and covariance matrices of regions around center c_u
- The probability a user u visiting a location l given C_u is defined as:

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



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:

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



Concluding Remarks

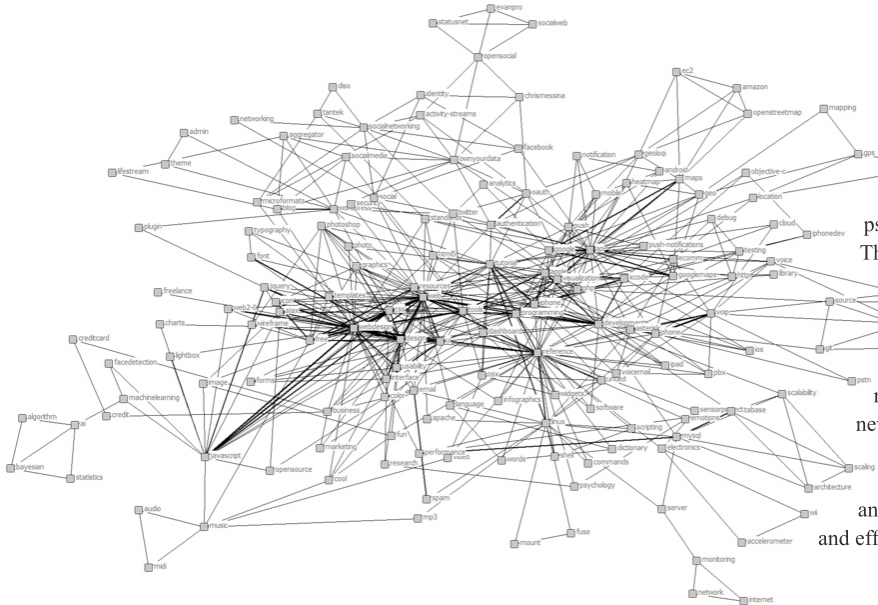
- **Social recommendation** extends traditional models and techniques by using **social graphs, ensembles, distrust relationships, clicks**, etc.
- Fusing of social behavior information, e.g., media consumption patterns, temporal relationships, etc.
- **Location recommendation** follows a similar path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



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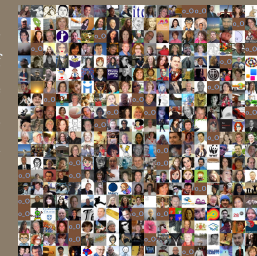
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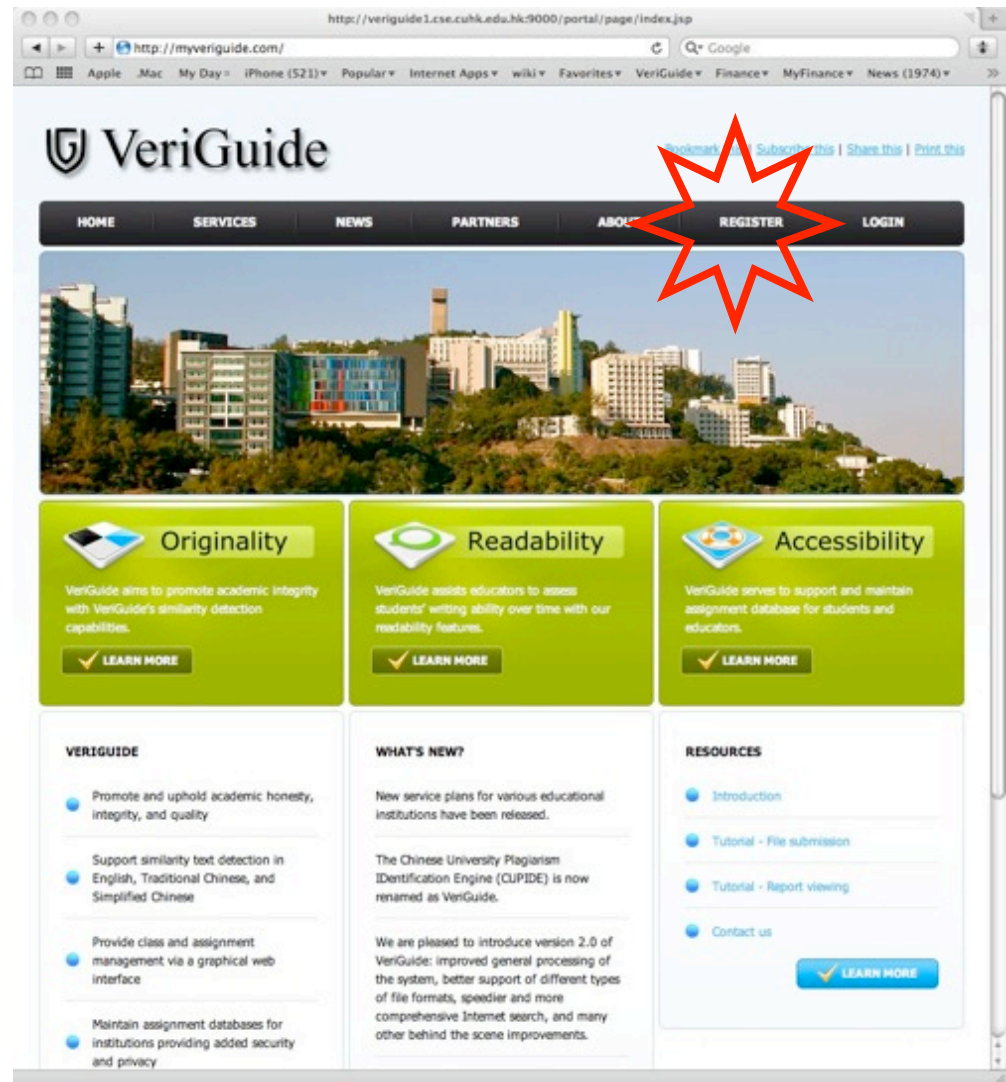
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- Recommender system: accurate recommendation based on sparse matrix ([SIGIR'07](#))
- SoRec: Social Recommendation Using Probabilistic Matrix Factorization ([CIKM'08](#))

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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Q & A

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