

# Recent Developments in Social and Location Recommendations

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Asia Modelling Symposium, July 23, 2013, Hong Kong



# Difficulties in Modelling



- What you see and what other see in you is different
- What you see and what we see in you is also different

<http://www.intomobile.com/2010/11/04/how-iphone-android-and-blackberry-users-see-each-other/>

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# Information and More Information!

flickr™



amazon.com.



You Tube

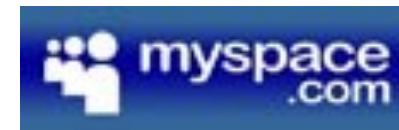


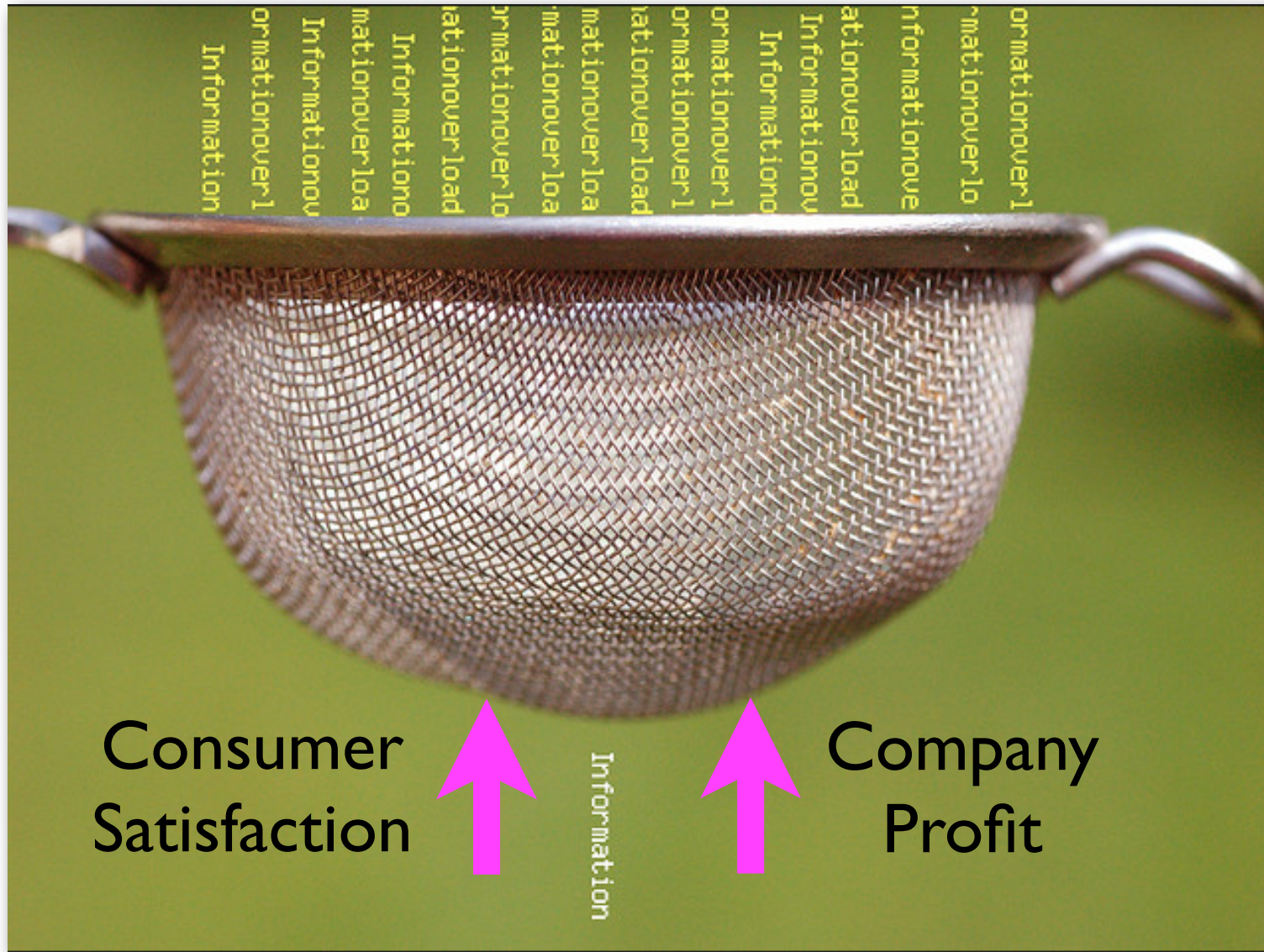
ebay

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# 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, a 20% discount from the list price of \$99.00. A 'Click to LOOK INSIDE!' button is positioned over the book cover image. To the right of the book details, there are buttons for 'Add to Cart', 'Add to Cart with FREE Two-Day Shipping', and 'Add to Wish List'. A 'More Buying Choices' section indicates that 31 used and new copies are available for \$14.62. At the bottom of the product page, a red oval highlights the text 'Customers Who Bought This Item Also Bought', with a small book cover for 'Social Web' visible below it.

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# Real Life Examples

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

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](#)  
[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!

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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!



# 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]



# 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 represents user-specific latent feature vectors, with a blue arrow pointing to the label "User-specific latent feature vector". The second matrix represents item-specific latent feature column vectors, with 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 Receive Recommendations by Email



[Watch the Trailer](#)

## My Blueberry Nights (2008)

<b>The Critics:</b> <b>B-</b> <a href="#">7 reviews</a>	<b>My Grade:</b> <b>A+</b> Oscar-worthy <a href="#">write a review</a>	<b>A</b>
		<b>B</b>
		<b>C</b>
		<b>D</b>
		<b>F</b>

**Yahoo! Users:**  
**B-**  
[667 ratings](#)



[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

[See All Recommendations](#)



# Challenges

## My Movie Ratings



**The Pursuit of Happyness** (PG-13, 1 hr. 57 min.)

Buy DVD | Add to My Lists

Yahoo! Users: **B+** 38992 ratings

The Critics: **B-** 13 reviews

★ My Rating: A+



**Finding Nemo** (G, 1 hr. 40 min.)

Buy DVD | Add to My Lists

Yahoo! Users: **B+** 137394 ratings

The Critics: **A-** 14 reviews

★ My Rating: A



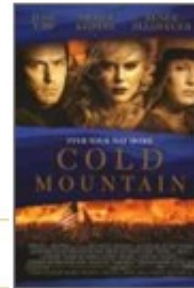
**My Blueberry Nights** (PG-13, 1 hr. 30 min.)

Buy DVD | Add to My Lists

Yahoo! Users: **B-** 756 ratings

The Critics: **B-** 7 reviews

★ My Rating: A+



**Cold Mountain** (R, 2 hrs. 35 min.)

Buy DVD | Add to My Lists

Yahoo! Users: **B** 38986 ratings

The Critics: **B+** 10 reviews

★ My Rating: B+



**The Lord of the Rings: The Fellowship of the Ring**

Buy DVD | Add to My Lists

Yahoo! Users: **A-** 110957 ratings

The Critics: **A** 15 reviews

★ My Rating: A



**Shrek 2** (PG, 1 hr. 32 min.)

Buy DVD | Add to My Lists

Yahoo! Users: **B+** 150368 ratings

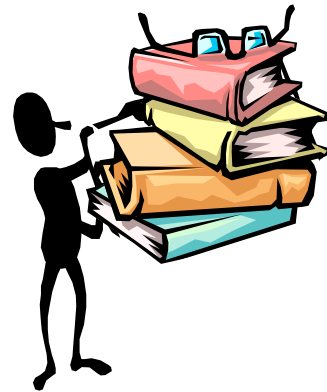
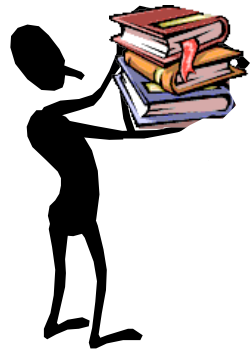
The Critics: **B** 15 reviews

★ My Rating: B



# Challenges

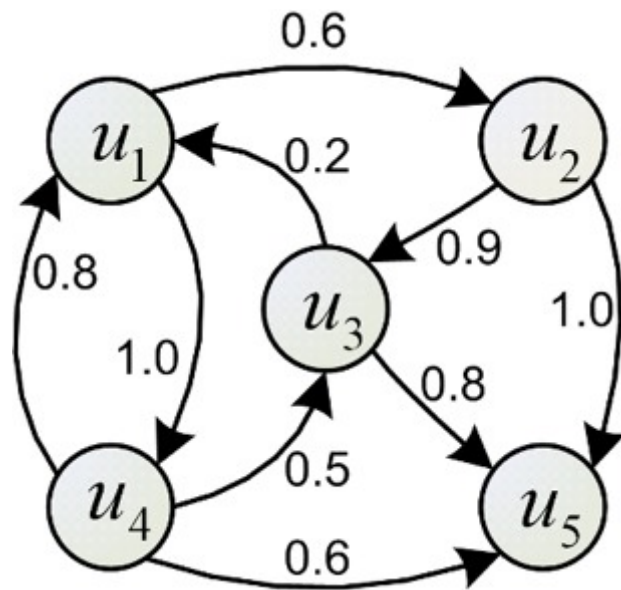
- Traditional recommender systems ignore the social connections between users



Recommendations  
from friends



# Problem Definition



Social Trust Graph

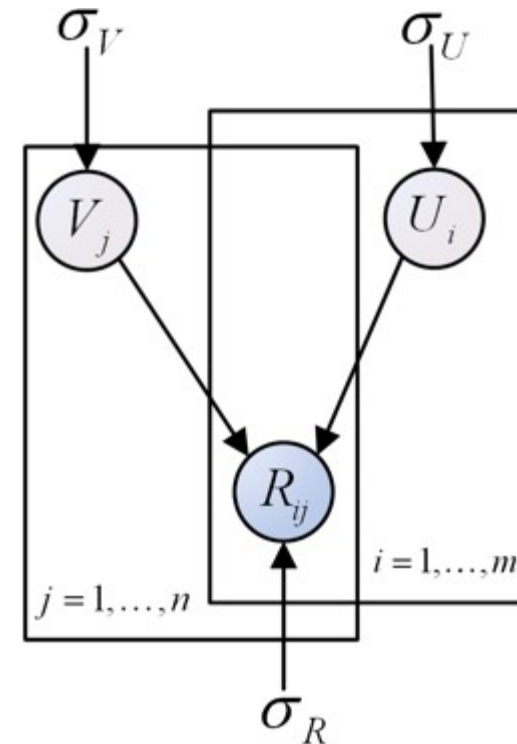
	$v_1$	$v_2$	$v_3$	$v_4$	$v_5$	$v_6$
$u_1$		5	2		3	
$u_2$	4			3		4
$u_3$			2			2
$u_4$	5			3		
$u_5$		5	5			3

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



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

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

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

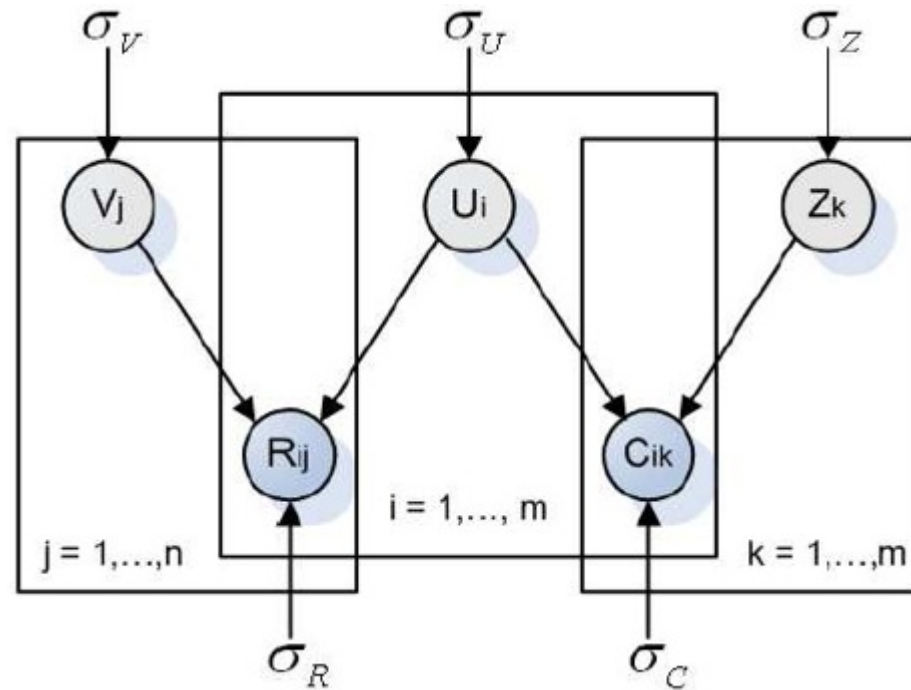
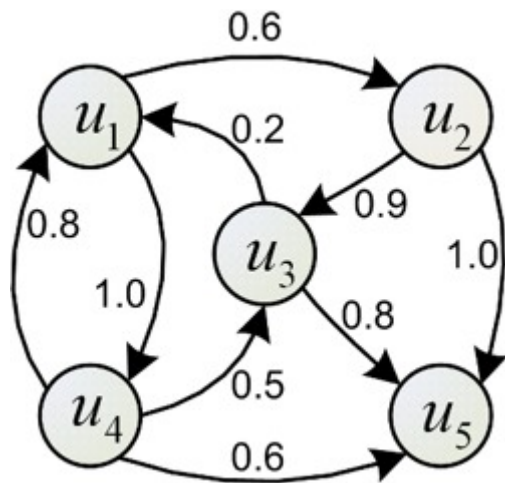
R. Salakhutdinov and A. Mnih (NIPS'08)

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Asia Modelling Symposium, July 23, 2013, Hong Kong



# SoRec

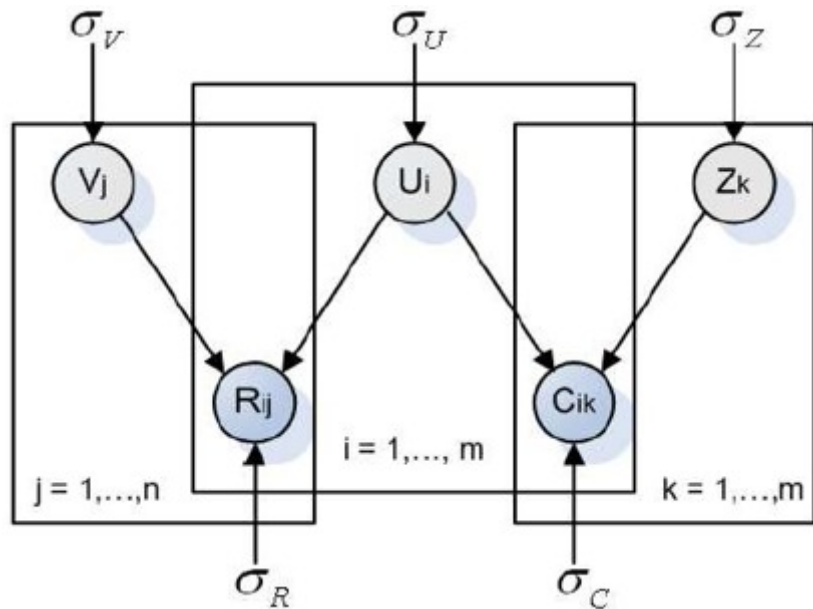
	$v_1$	$v_2$	$v_3$	$v_4$	$v_5$	$v_6$
$u_1$		5	2		3	
$u_2$	4			3		4
$u_3$			2			2
$u_4$	5			3		
$u_5$		5	5			3



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

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

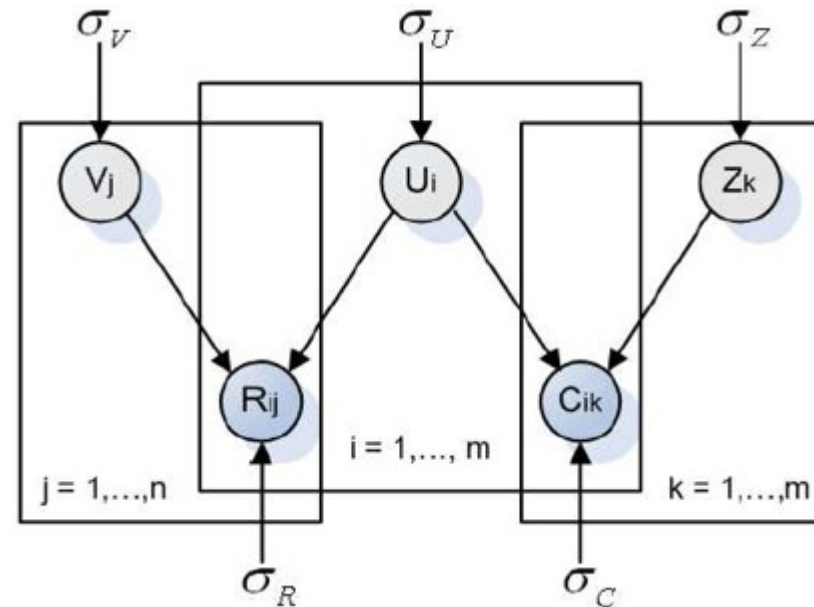
$$\frac{\partial \mathcal{L}}{\partial V_j} = \sum_{i=1}^m I_{ij}^R g'(U_i^T V_j) (g(U_i^T V_j) - r_{ij}) U_i + \lambda_V V_j,$$

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



# Disadvantages of SoRec

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



SoRec



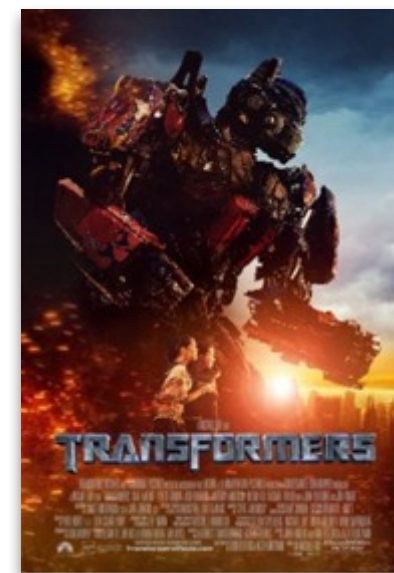
# Learning to Recommend with Social Trust Ensemble

[Ma et al., SIGIR2009]



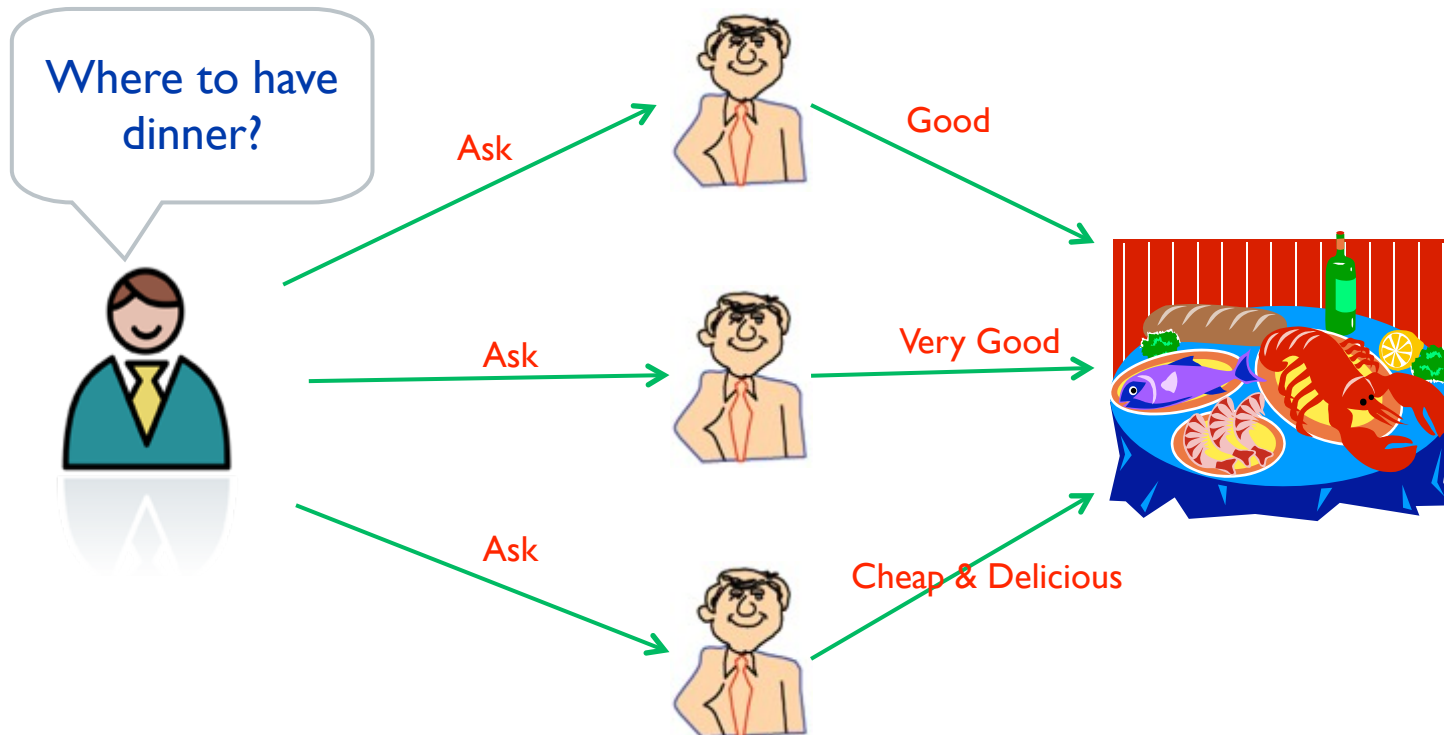
# 1<sup>st</sup> Motivation

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



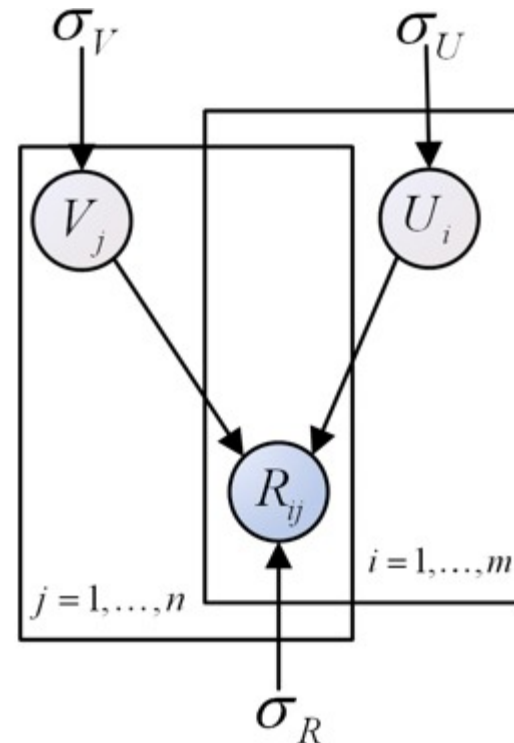
# 2<sup>nd</sup> Motivation

- 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]

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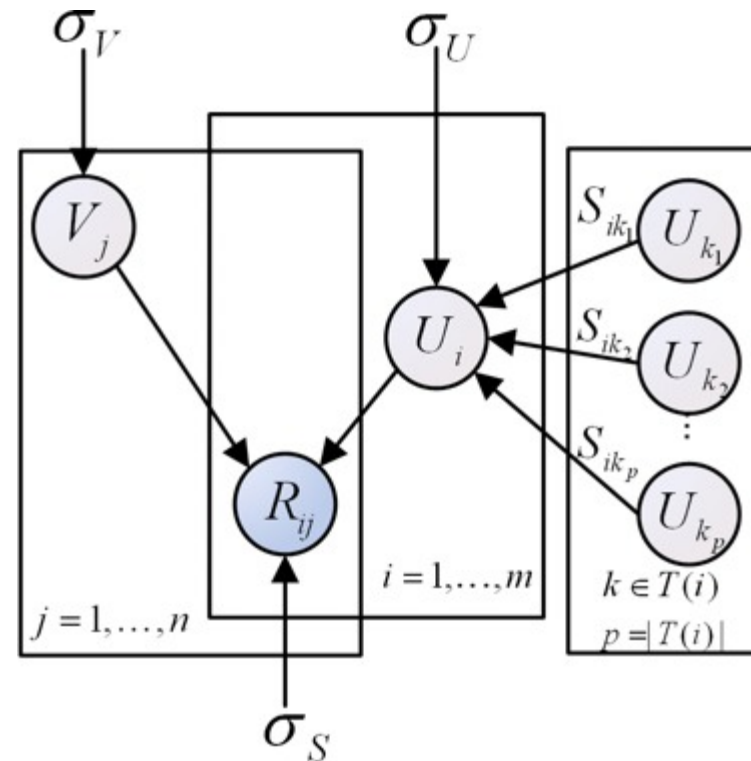
# Recommendations by Trusted Friends

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

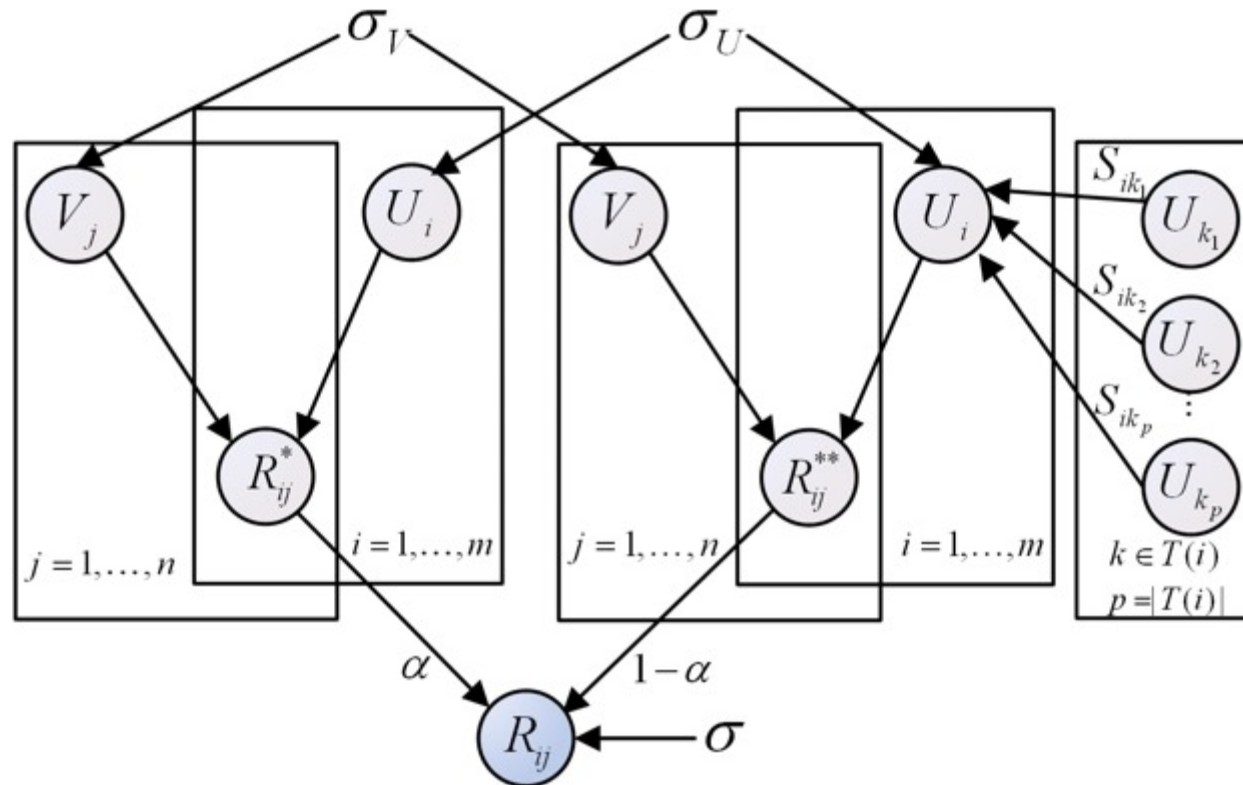
$$\hat{R}_{ik} = \sum_{j \in \mathcal{T}(i)} R_{jk} S_{ij}$$

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

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



# 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 More | MSN Hotmail", a search bar containing "sigir", and a user profile for "Irwin" with "Sign out" and "Rewards" options. The location is "Walnut Creek, California" and there are "Preferences" links. A notification for Irwin's Facebook friends is visible. The search results are categorized under "ALL RESULTS" and show "1-10 of 255,000 results". The results list includes:

- Welcome to SIGIR | Home**: An Iraqi fisherman pushes his boat off-shore to depart on his daily fishing trip. View the Report. [www.sigir.mil](http://www.sigir.mil)
- ACM SIGIR Special Interest Group on Information Retrieval Home Page**: Welcome to the ACM SIGIR Web site. ACM SIGIR addresses issues ranging from theory to user demands in the application of computers to the acquisition, organization ... [www.sigir.org](http://www.sigir.org)
- home [ACM SIGIR 2010]**: ACM-SIGIR 2010 was held at UniMail, Geneva, Switzerland between 19th and 23rd of July 2010. Thanks to all the participants!!! The story continues with ACM-SIGIR 2011. [www.sigir2010.org](http://www.sigir2010.org)
- Welcome to The 34th Annual ACM SIGIR Conference**: Important Dates. 17 Jan 2011 : Abstracts for full research papers due; 24 Jan 2011 : Full research paper submissions due; 28 Jan 2011 : Workshop proposals due [sigir2011.org](http://sigir2011.org)
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On the left side, there are sections for "RELATED SEARCHES" (Special Inspector General for Iraq Reconstruction, SIGIR Reports, SIGIR Poster, SIGIR List, SIGIR 2011, SIGIR 10, SIGIR 2010 Registration, SIGIR 2009 Proceedings), "SEARCH HISTORY" (Search more to see your history, See all, Clear all · Turn off), and "NARROW BY DATE" (All results, Past 24 hours, Past week, 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”



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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

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

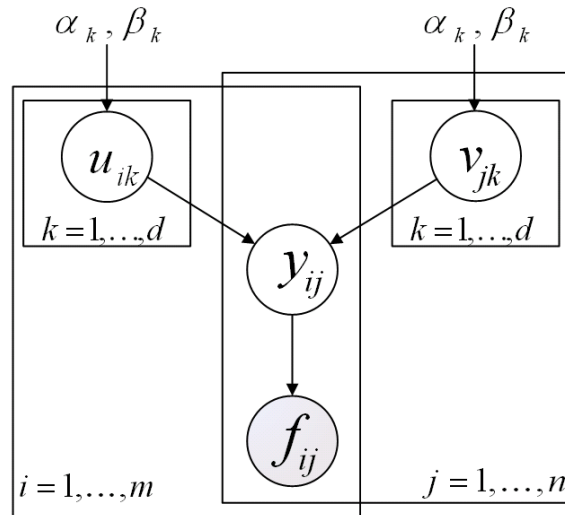
$$p(R|U, V, \sigma_R^2) = \prod_{i=1}^m \prod_{j=1}^n \left[ \mathcal{N}(R_{ij} | U_i V_j^T, \sigma_R^2) \right]^{I_{ij}}$$

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

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



# 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

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

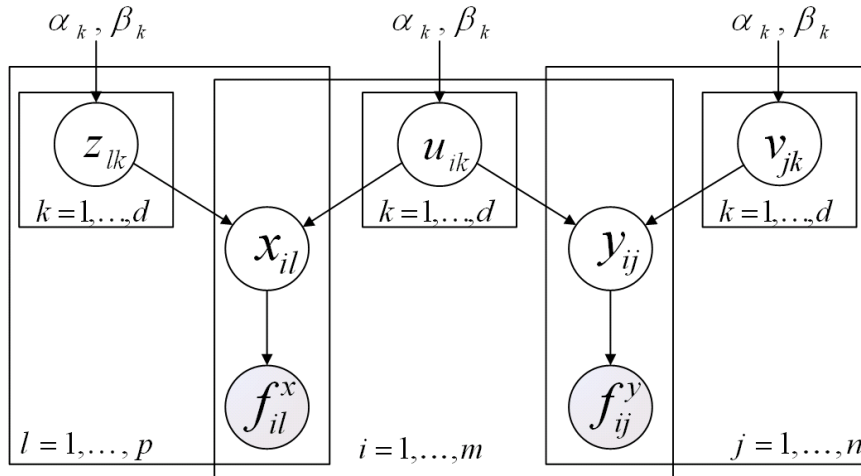
$$u_{ik} \leftarrow u_{ik} \frac{\sum_{j=1}^n (f_{ij} v_{jk} / y_{ij}) + (\alpha_k - 1) / \beta_k}{\sum_{j=1}^n v_{jk} + 1 / \beta_k}$$

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





# Collective Probabilistic Factor Model



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

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

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

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

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

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

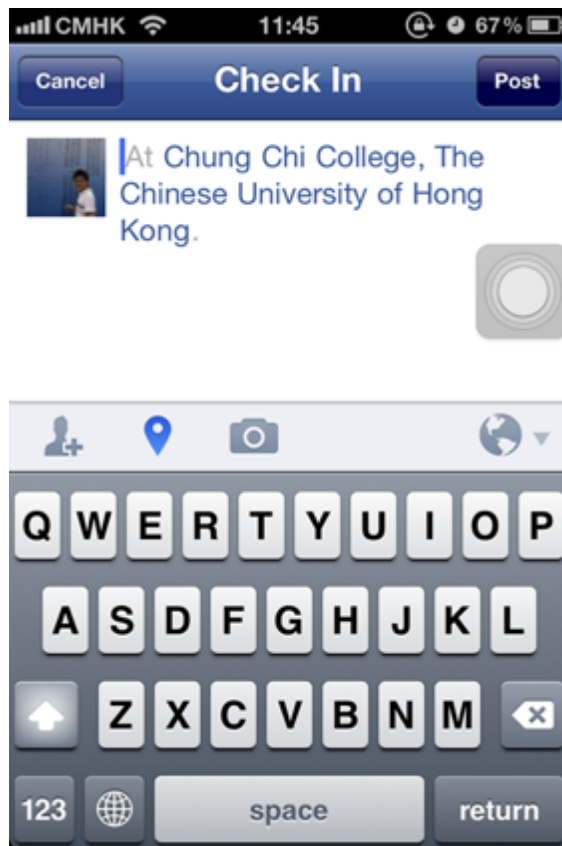


# Location Recommendations

[Cheng et al., AAI 2012]



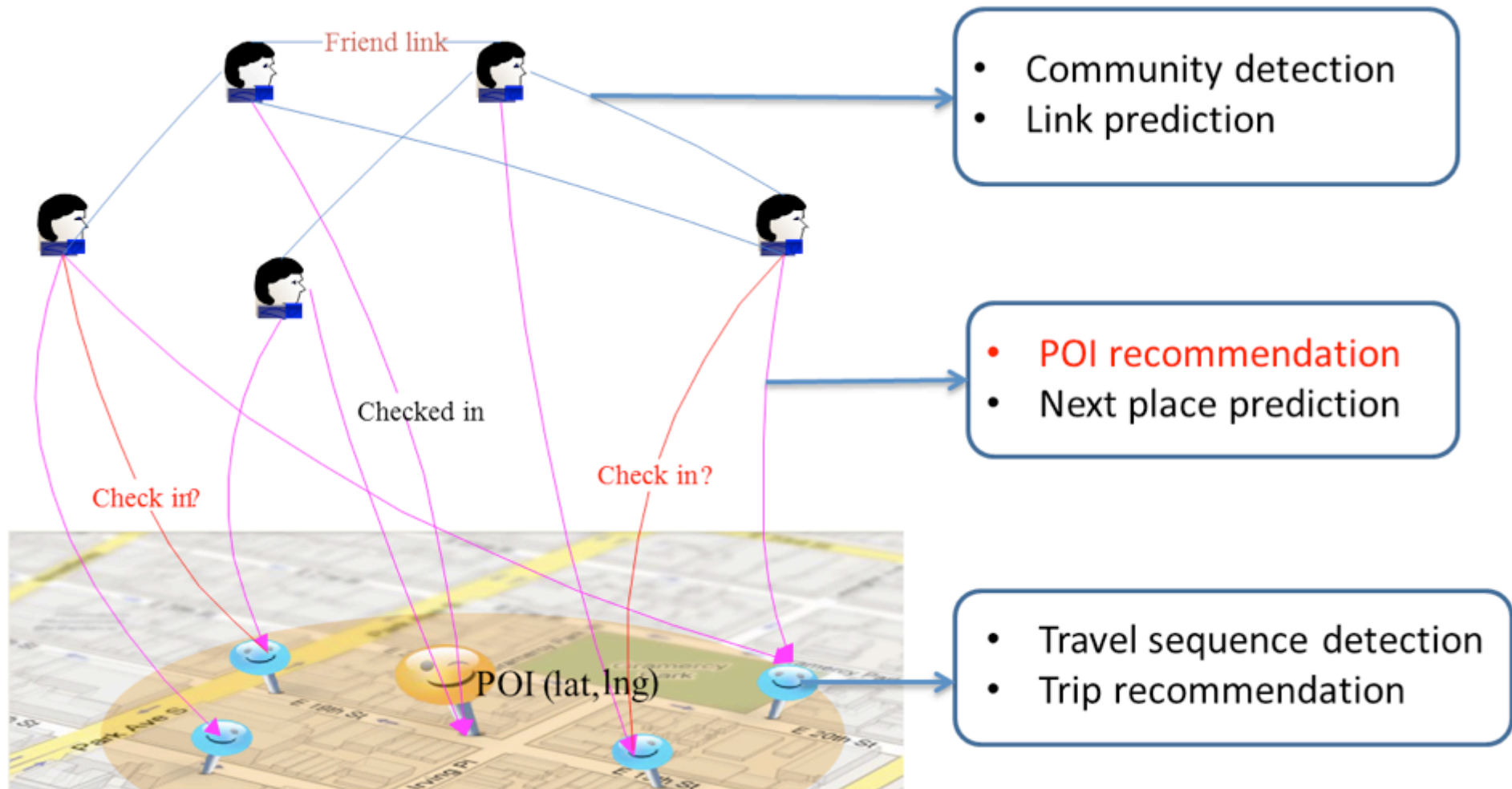
# Check Out on “Check-ins”



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# Location-based Social Networks (LBSNs)



# Motivations

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

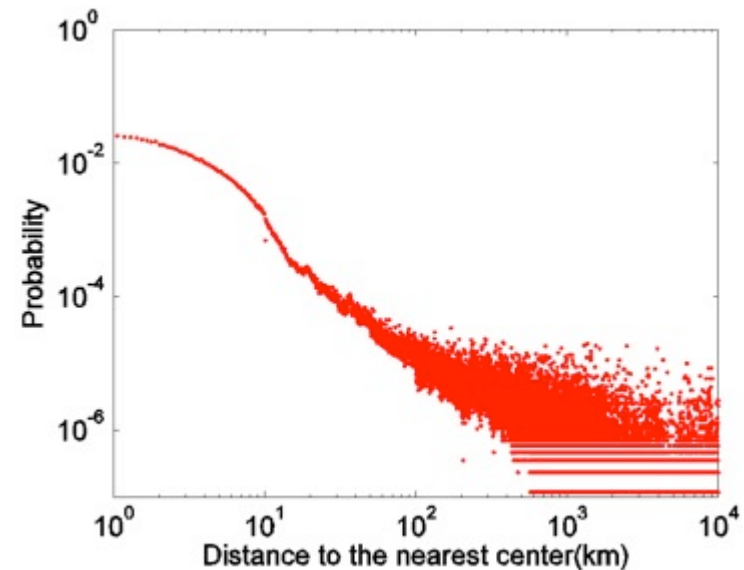
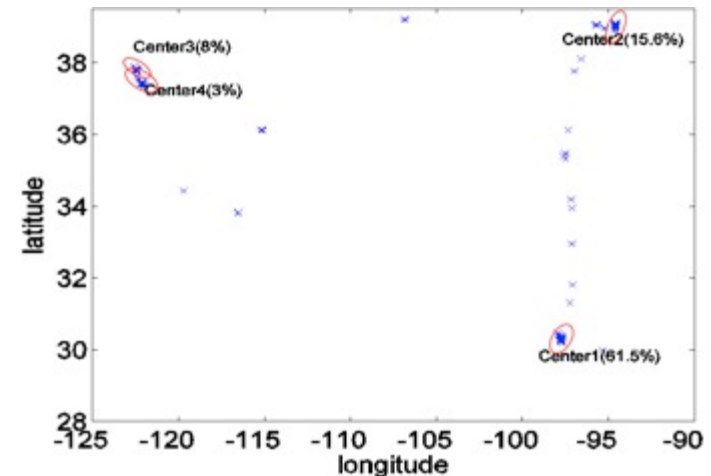


- The check-in probability is sensitive to **geographical influence**.



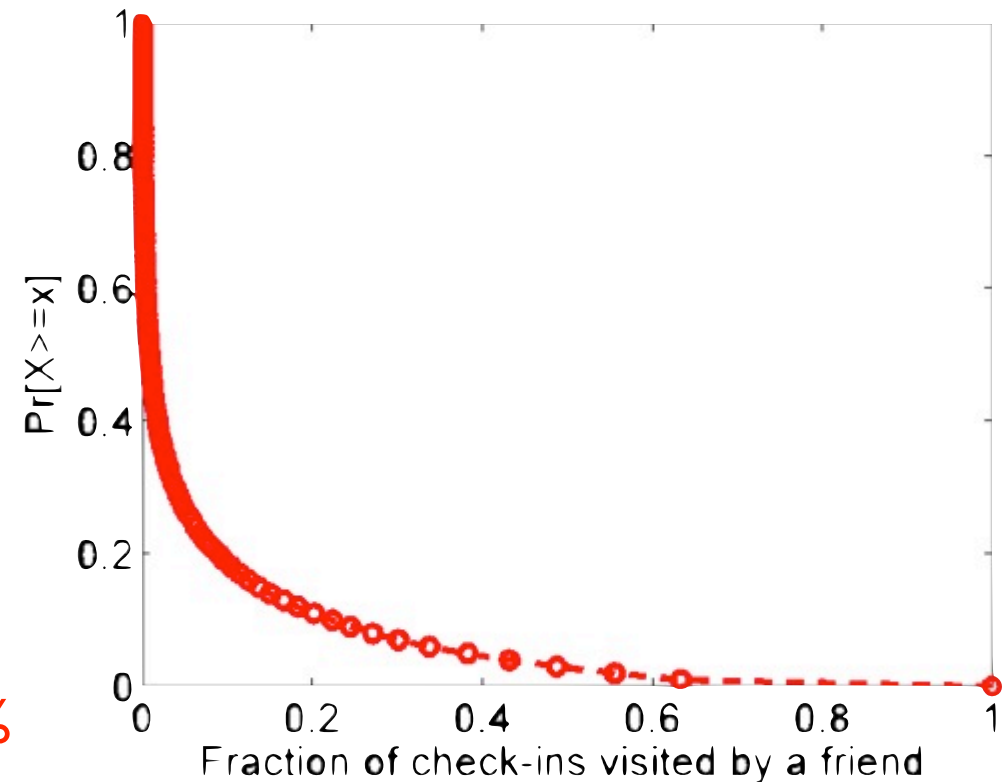
# Observation #1

- 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





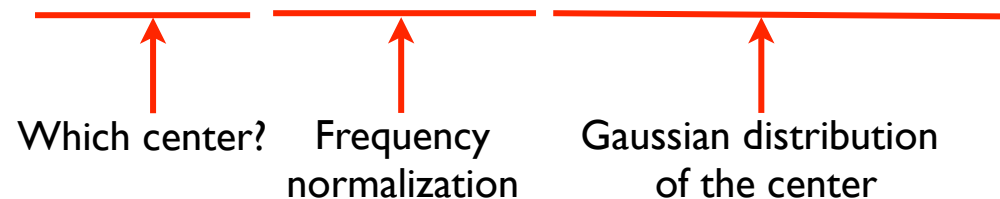
# Multi-center Gaussian Model

- 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  $c_u$

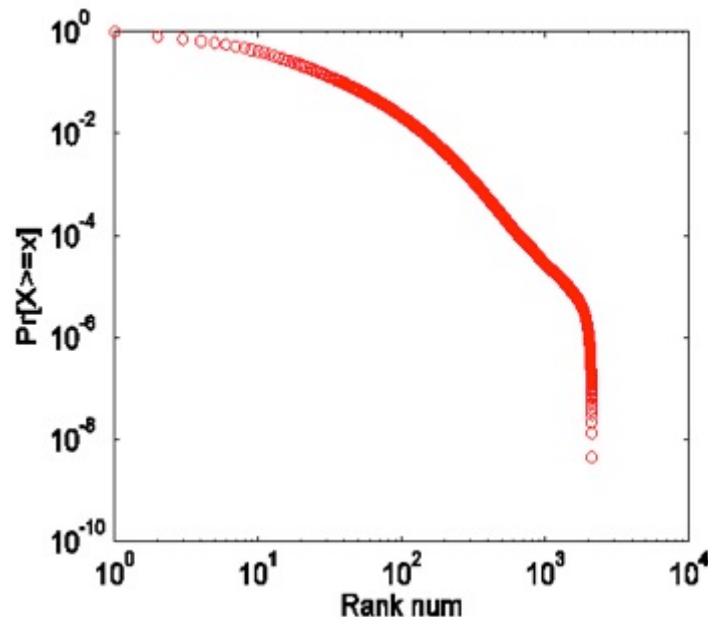
- The probability a user  $u$  visiting a location  $l$  given  $C_u$  is defined as:

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



# 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  $i = 1 \rightarrow |\mathcal{L}|$  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  $j = i + 1 \rightarrow |\mathcal{L}|$  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

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# Concluding Remarks

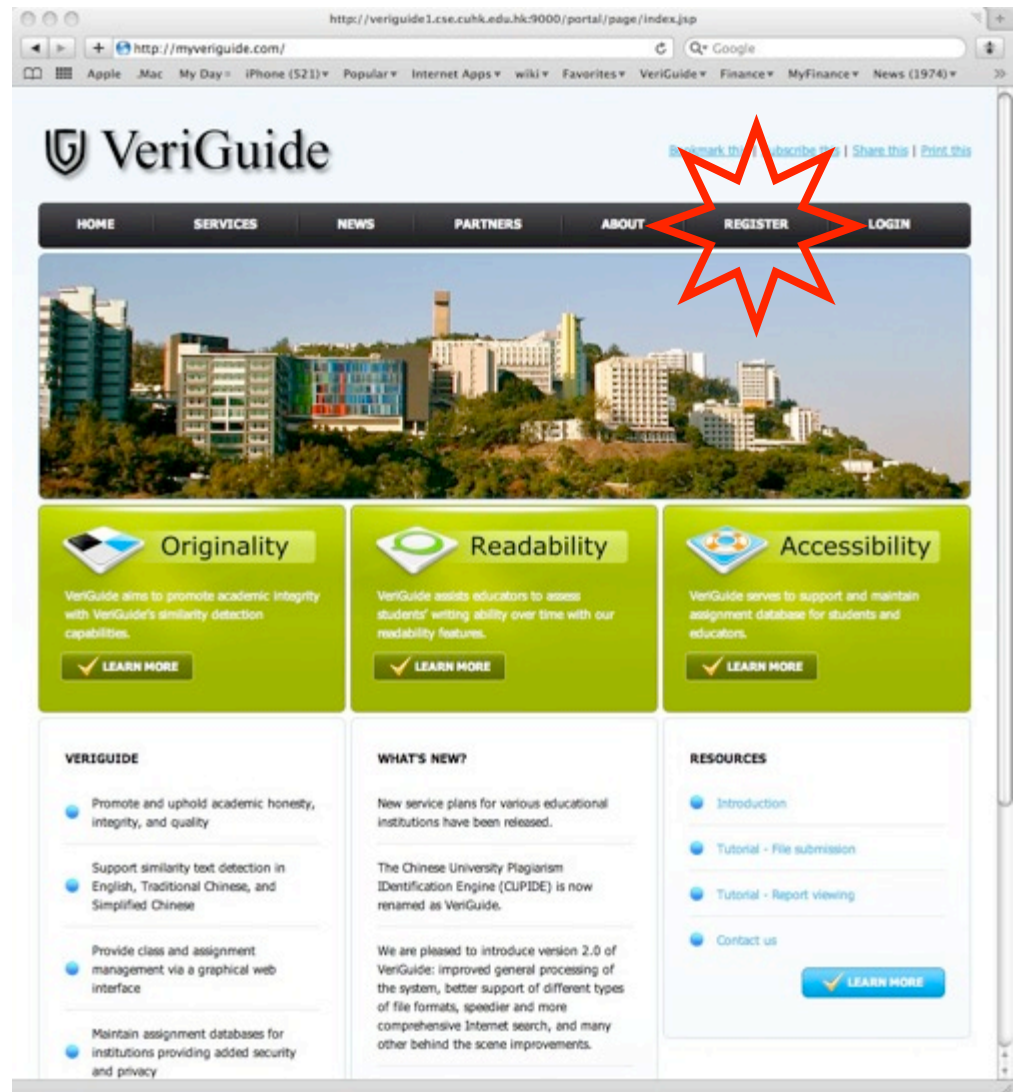
- Both social and location recommendation play a significant role in the social web!
- **Social recommendation** extends traditional models and techniques by using **social graphs, ensembles, distrust relationships, clicks**, etc.
- Fusing of social behavior information, e.g., media consumption patterns,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





# VeriGuide

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*"...the truth shall set you free.", Caltech Motto*

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- [Associate Editor](#) of ACM Transactions on Knowledge Discovery from Data ([ACM TKDD](#))
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<http://www.cse.cuhk.edu.hk/~king>  
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Asia Modelling Symposium, July 23, 2013, Hong Kong



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- Hongyi Zhang (Ph.D.)
- Chao Zhou (Ph.D.)
- Patrick Lau
- Raymond Yeung





# On-Going Research

## Machine Learning

- Can Irrelevant Data Help Semi-supervised Learning, Why and How? (CIKM'11)
- 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)

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# On-Going Research

## Web Intelligence/Information Retrieval

- Question Identification on Twitter ([CIKM'11](#))
- 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](#))

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# On-Going Research

## Recommender Systems/Collaborative Filtering

- Fused Matrix Factorization with Geographical and Social Influence in Location-based Social Networks ([AAAI'12](#))
- 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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# Q & A

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