Recent Developments in Social and Location Recommendations

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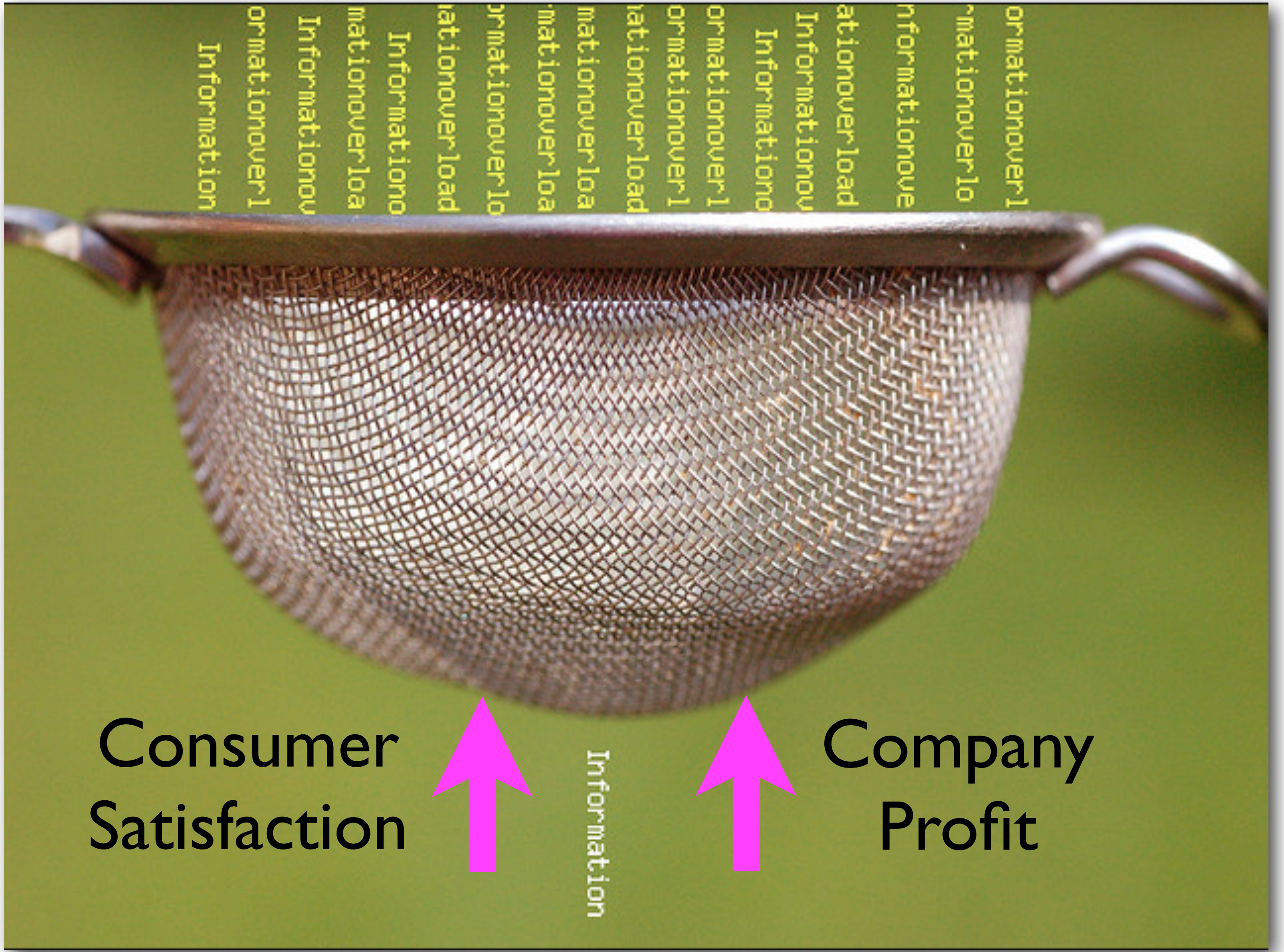
Difficulties in Modelling

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

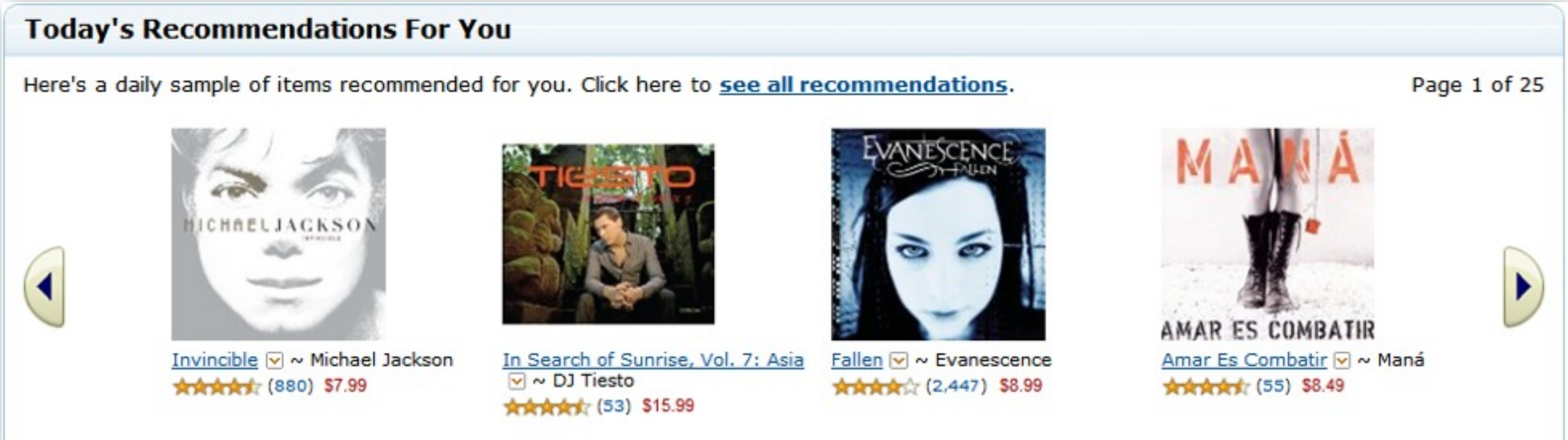
http://www.intomobile.com/2010/11/04/how-iphone-android-and-blackberry-users-see-each-other/

Information and More Information!


Consumer
Satisfaction
Information
Company
Profit

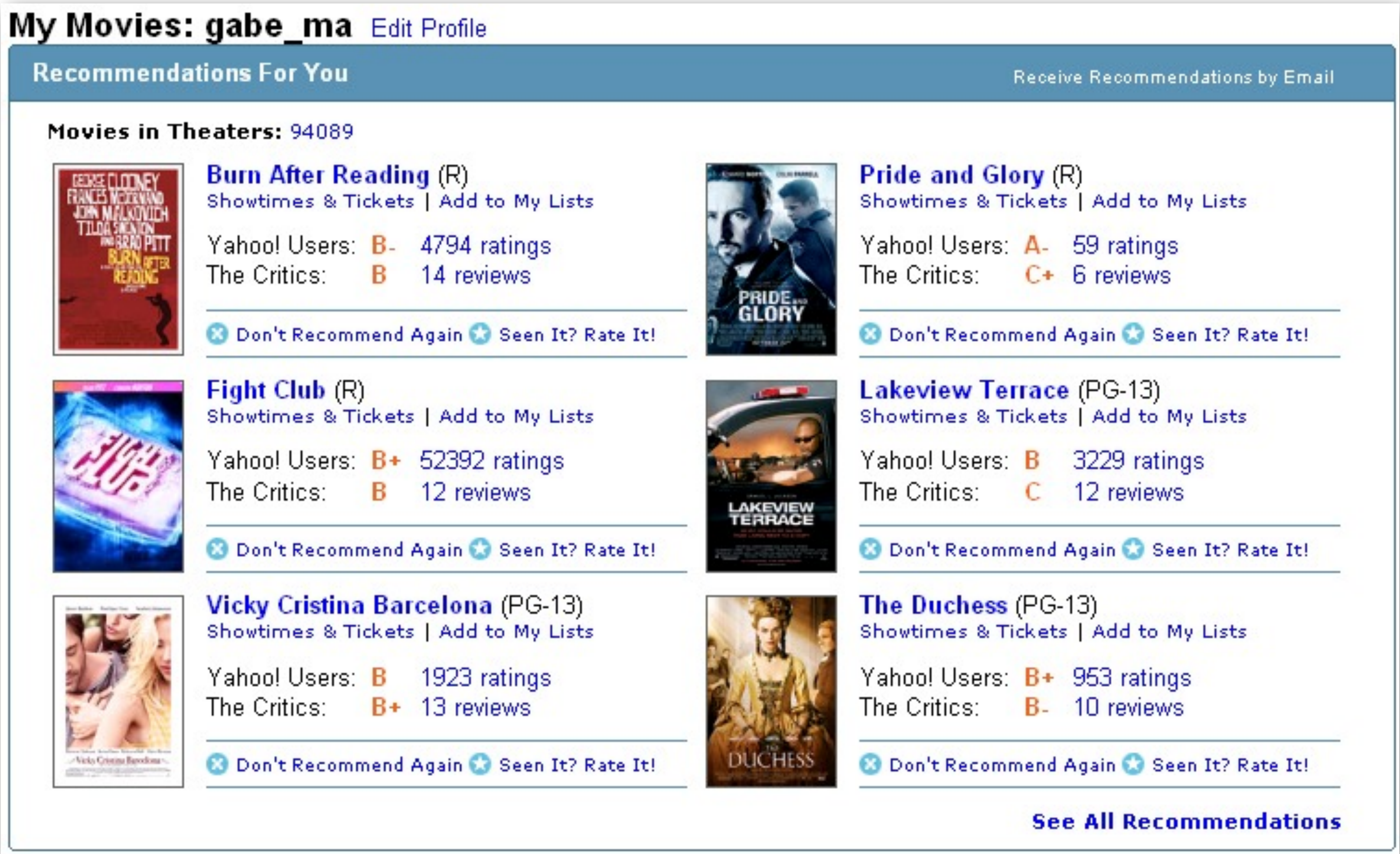
Real Life Examples

Real Life Examples



Real Life Examples

YAHOO! MOVIES



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

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

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

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

where $\lambda_1, \lambda_2 > 0$.

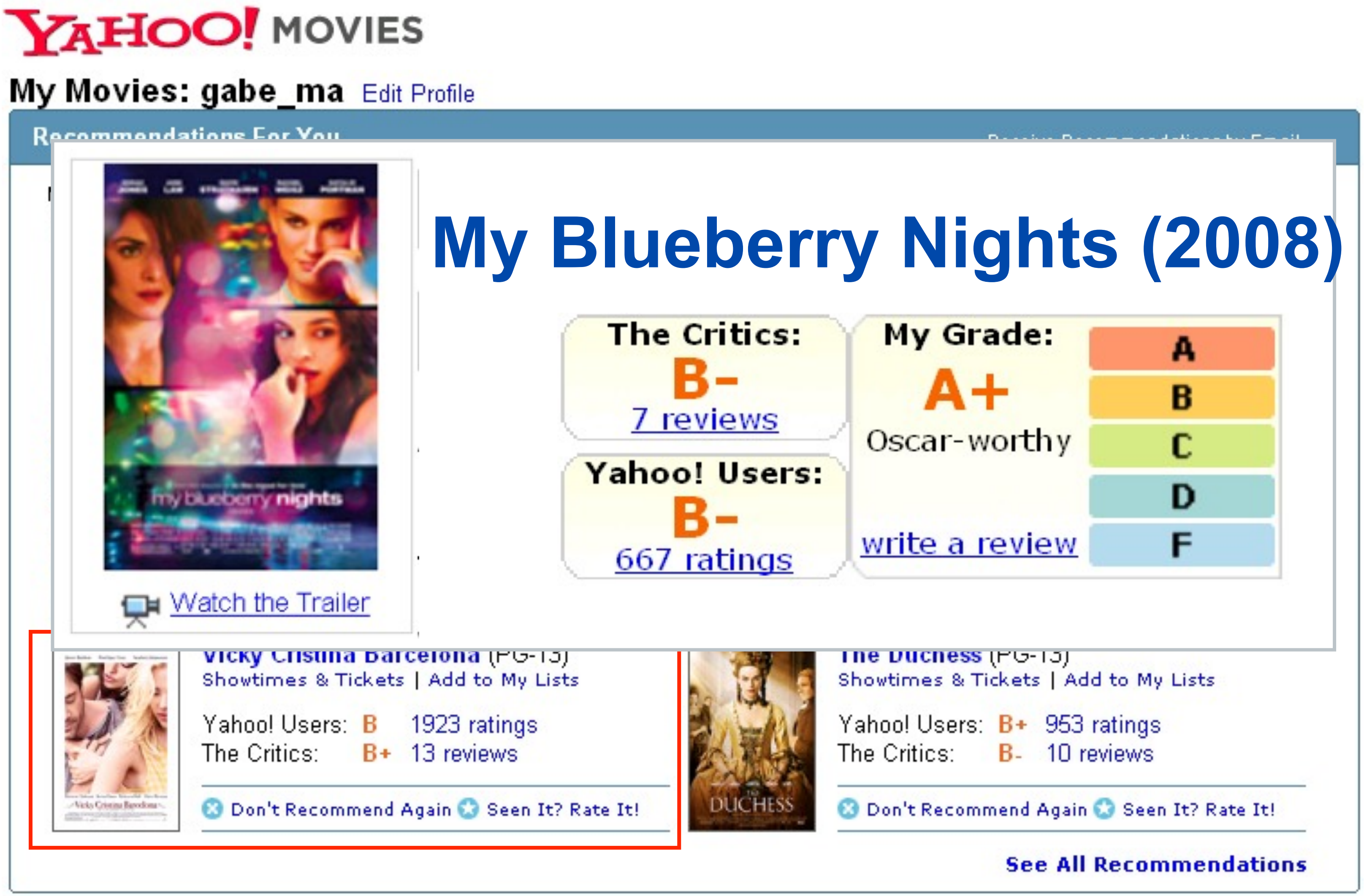
- The problem can be solved by simple gradient descent algorithm.

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

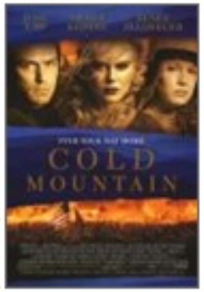
Yahoo! Users: B+ 137394 ratings
The Critics: A- 14 reviews

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

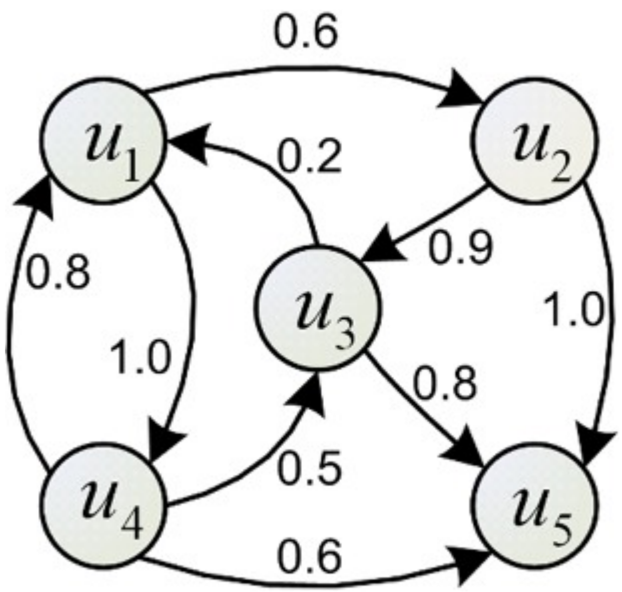
My Rating: B

Challenges

- Traditional recommender systems ignore the social connections between users

Recommendations from friends

Problem Definition



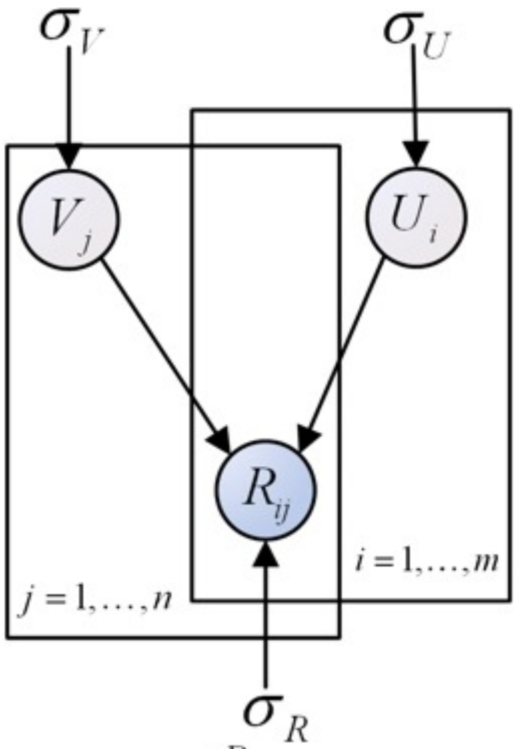
Social Trust Graph

	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



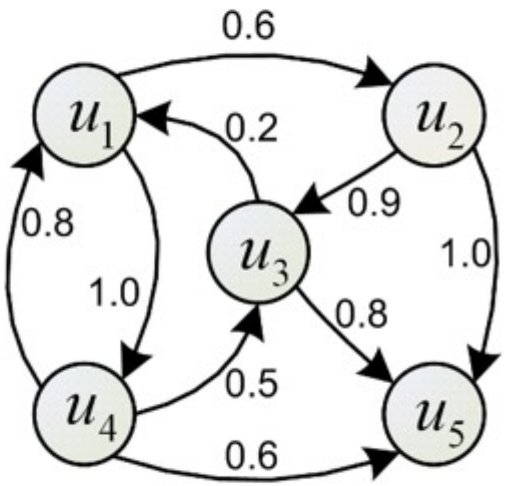
$$p(R|U, V, \sigma_R^2) = \prod_{i=1}^{m} \prod_{j=1}^{n} \left[\mathcal{N}\left(R_{ij} | g(U_i^T V_j), \sigma_R^2 \right) \right]^{I_{ij}^R}$$

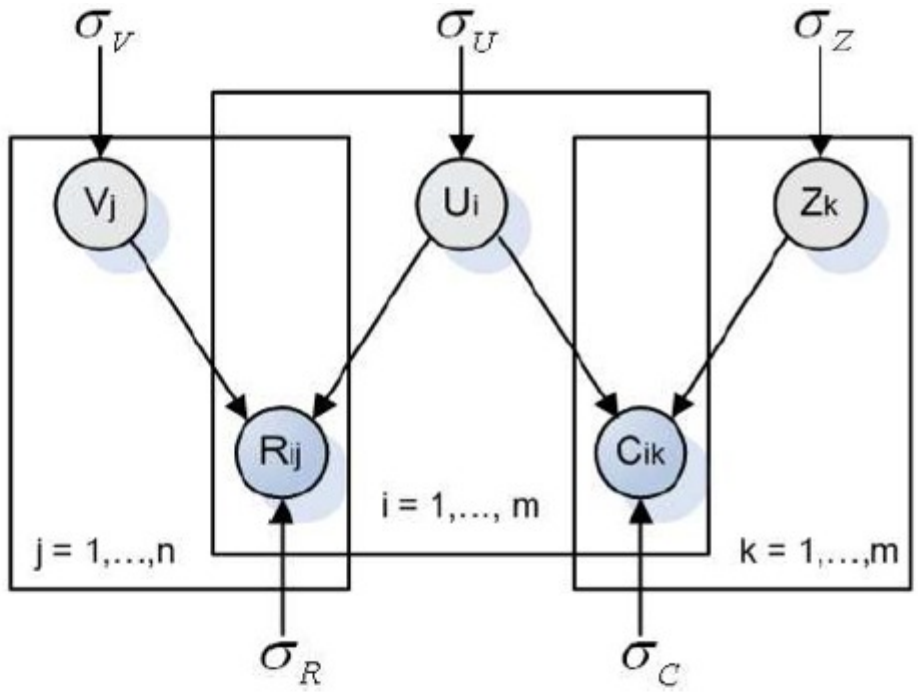
$$p(U|\sigma_U^2) = \prod_{i=1}^{m} \mathcal{N}(U_i | 0, \sigma_U^2 \mathbf{I}) \qquad p(V|\sigma_V^2) = \prod_{j=1}^{n} \mathcal{N}(V_j | 0, \sigma_V^2 \mathbf{I})$$

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

SoRec

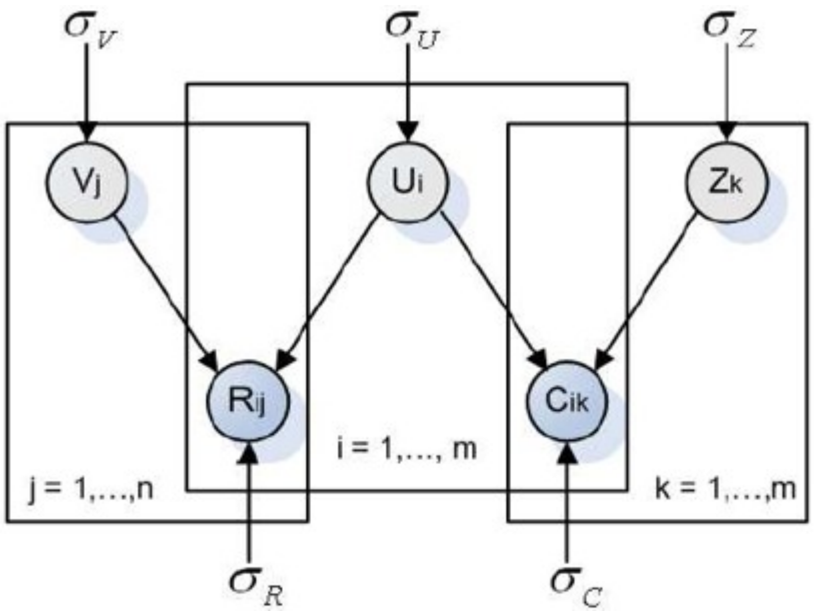
	v_1	v_2	v_3	v_4	v_5	v_6
u_1		5	2		3	
u_2	4			3		4
u_3			2			2
u_4	5			3		
u_5		5	5			3





SoRec

SoRec



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

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

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

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

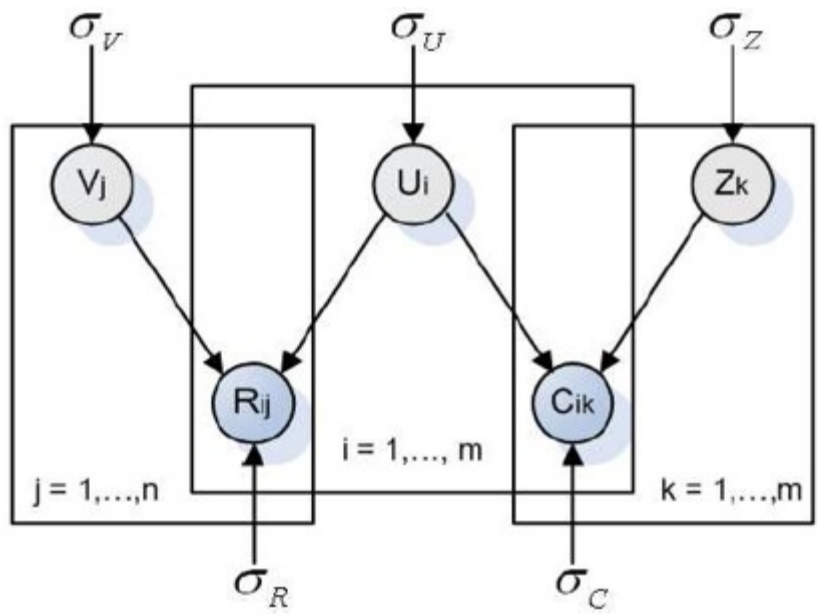
$$\mathcal{L}(R,C,U,V,Z) =$$
$$\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}^R(r_{ij}-g(U_i^T V_j))^2 + \frac{\lambda_C}{2}\sum_{i=1}^{m}\sum_{k=1}^{m} I_{ik}^C(c_{ik}^*-g(U_i^T Z_k))^2$$
$$+\frac{\lambda_U}{2}\|U\|_F^2 + \frac{\lambda_V}{2}\|V\|_F^2 + \frac{\lambda_Z}{2}\|Z\|_F^2,$$

SoRec

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

Disadvantages of SoRec

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



SoRec

Learning to Recommend with Social Trust Ensemble

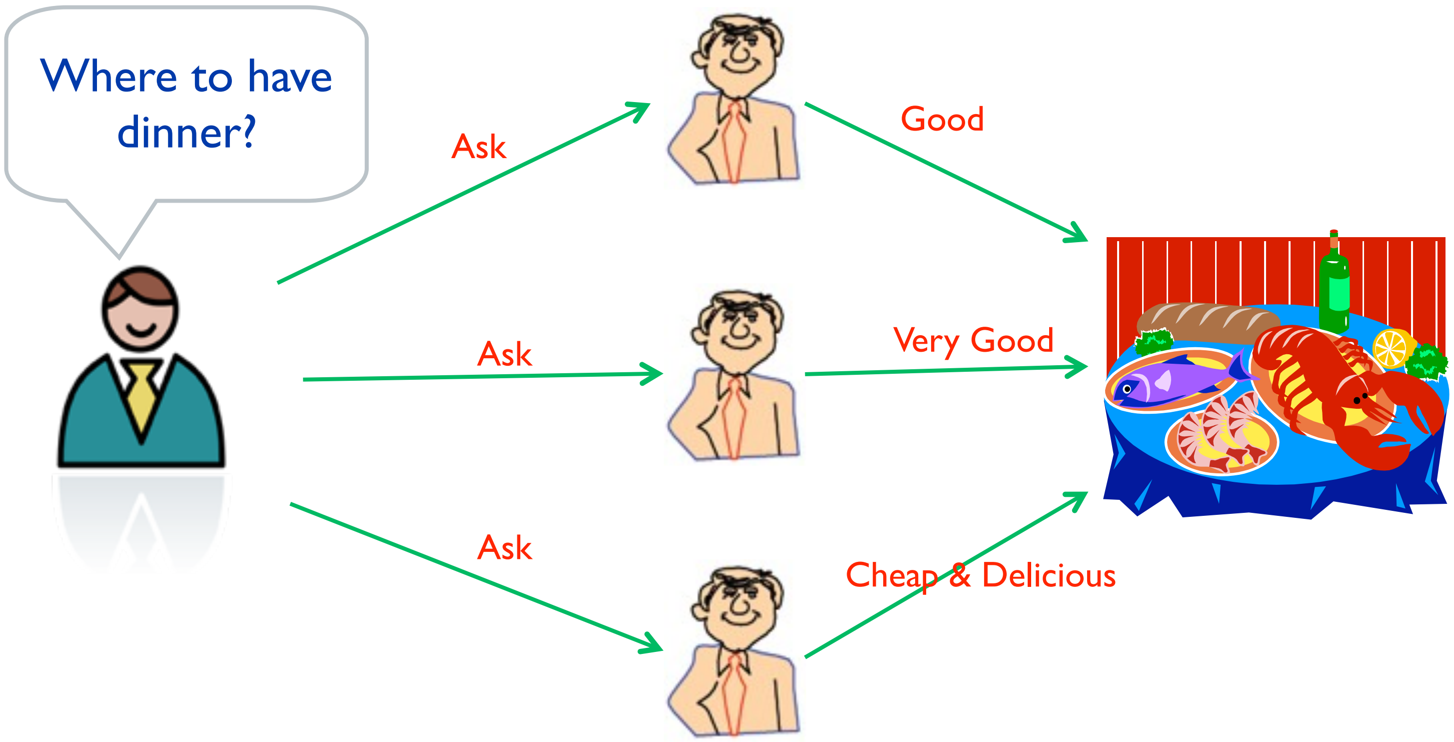
[Ma et al., SIGIR2009]

1st Motivation

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

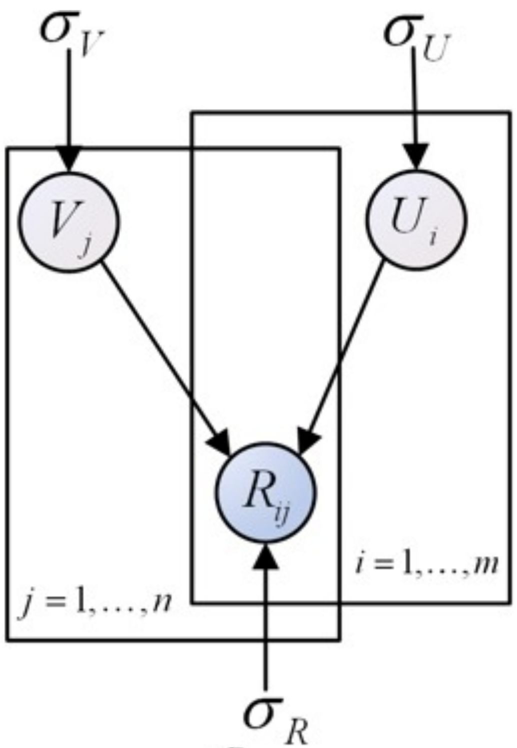
2nd Motivation

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



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



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

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

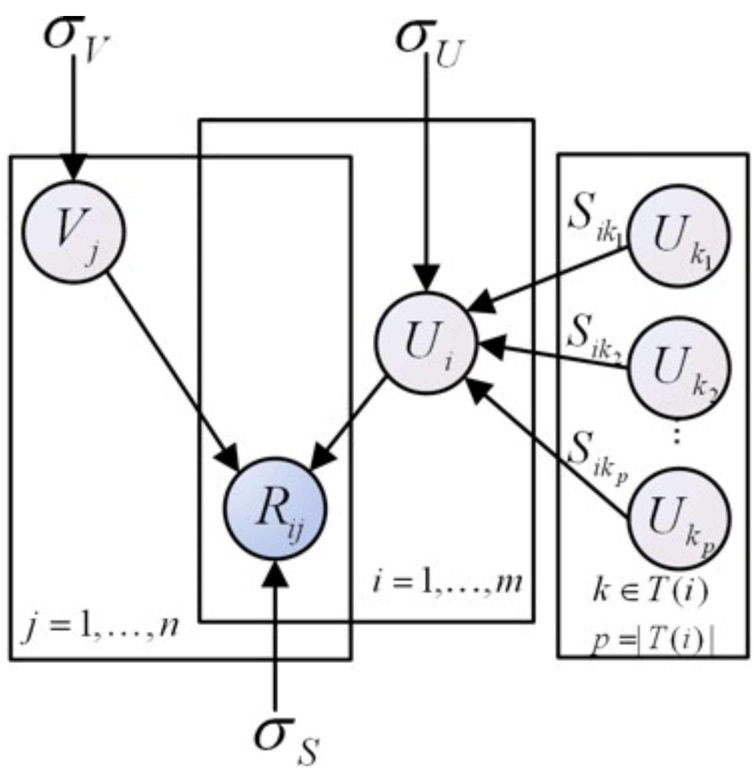
[R. Salakhutdinov, et al., NIPS2008]

Recommendations by Trusted Friends

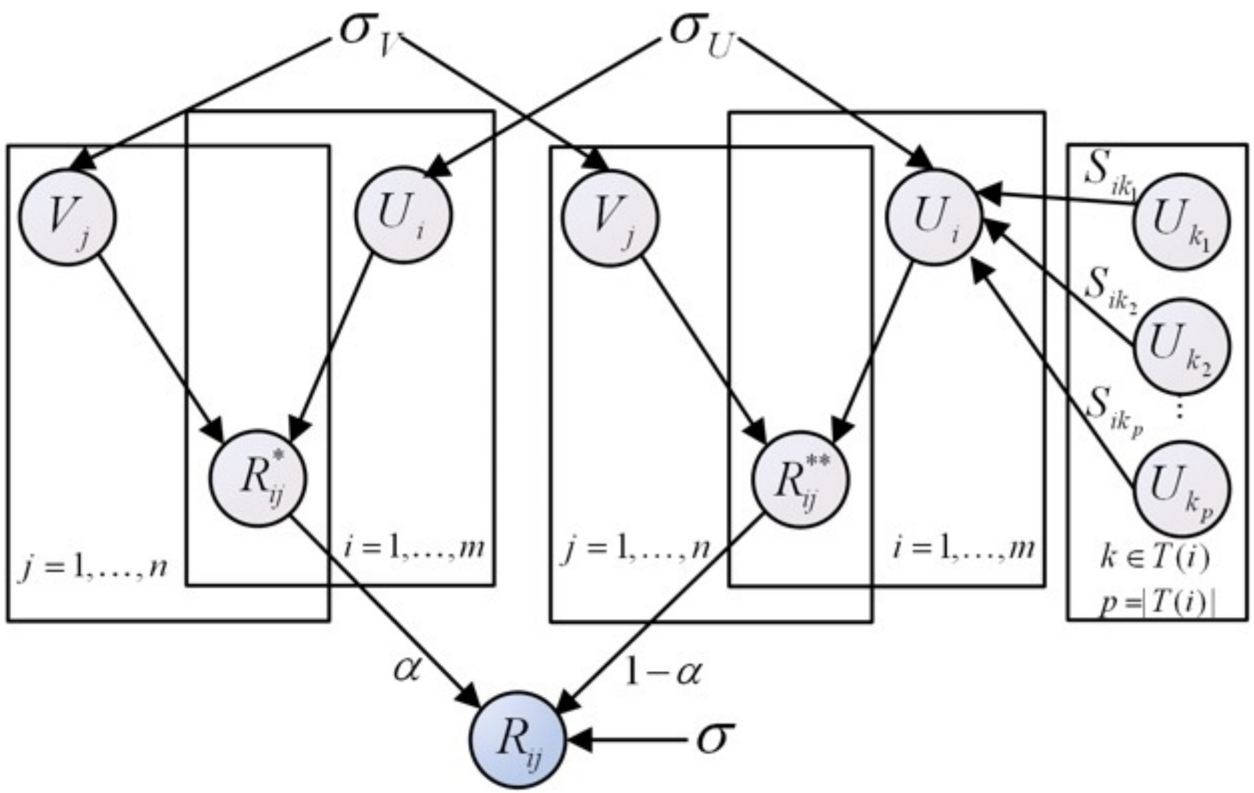
$$\widehat{R}_{ik} = \frac{\sum_{j \in \mathcal{T}(i)} R_{jk} S_{ij}}{|\mathcal{T}(i)|}$$

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

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



Recommendation with Social Trust Ensemble



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

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
  - 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

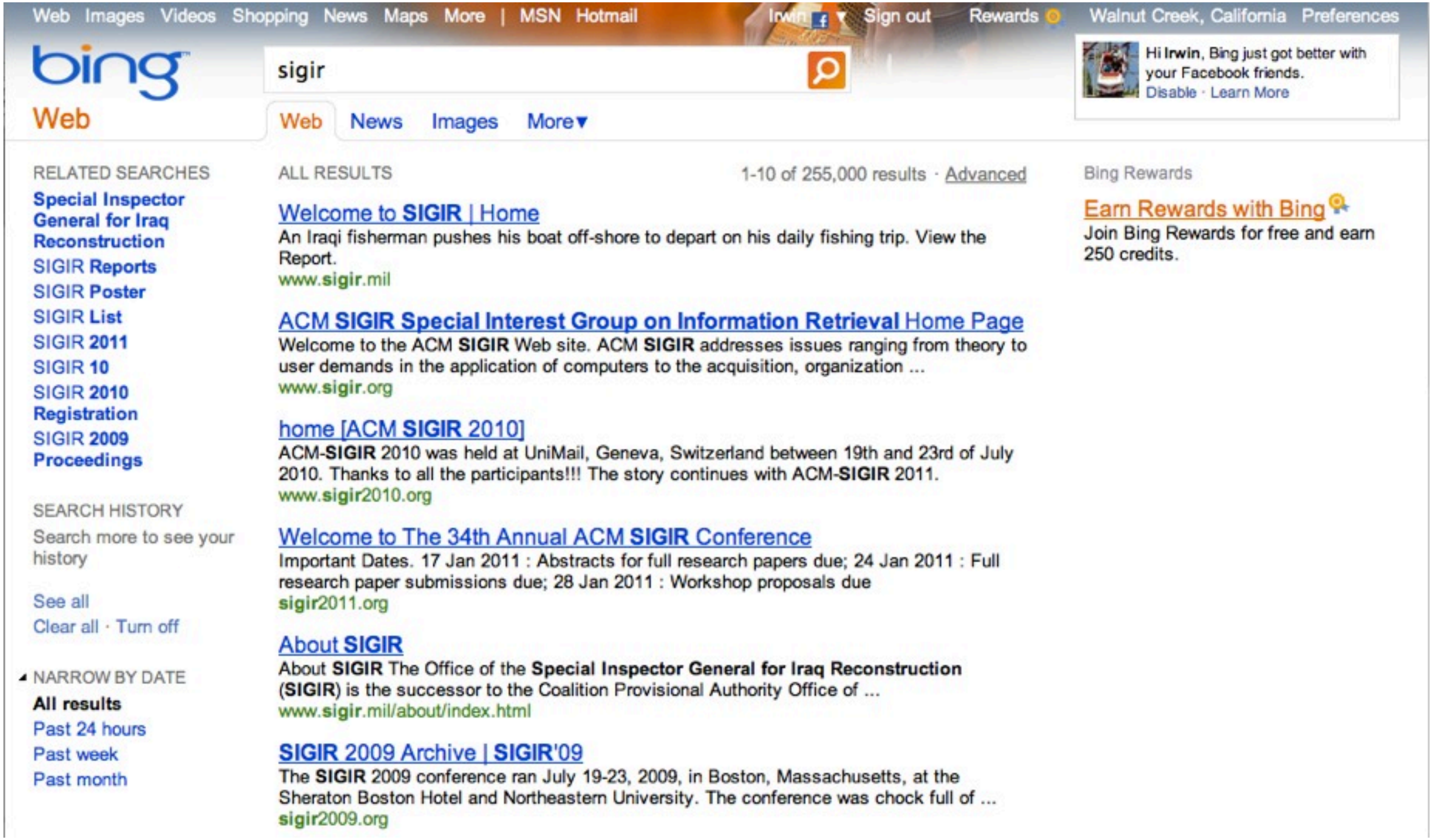
$$\min_{U} \frac{1}{2} \sum_{i=1}^{m} \sum_{t \in \mathcal{T}^{+}(i)} S_{it}^{\mathcal{T}} \|U_i - U_t\|_F^2$$

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

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

Matrix Factorization

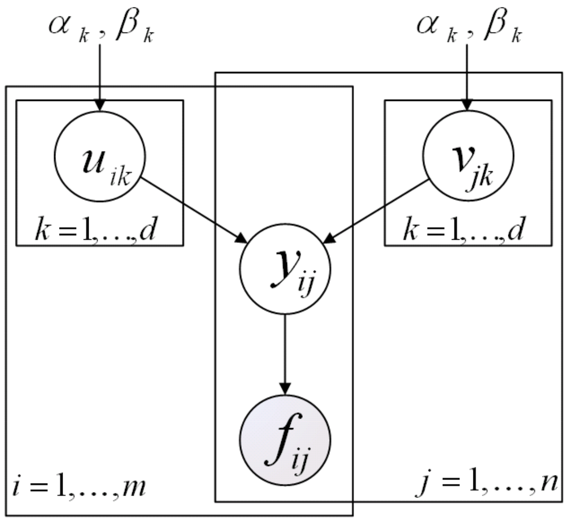
$$\min_{U,V} \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{n} I_{ij} (R_{ij} - U_i V_j^T)^2 + \frac{\lambda_1}{2} ||U||_F^2 + \frac{\lambda_2}{2} ||V||_F^2$$

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

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

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

Probabilistic Factor Model



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

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

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

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

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

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

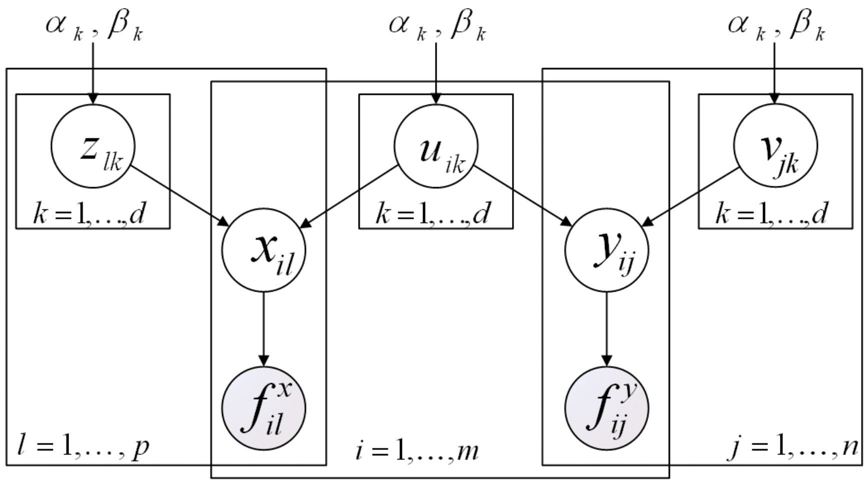
Probabilistic Factor Model

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

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

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

Collective Probabilistic Factor Model



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

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

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

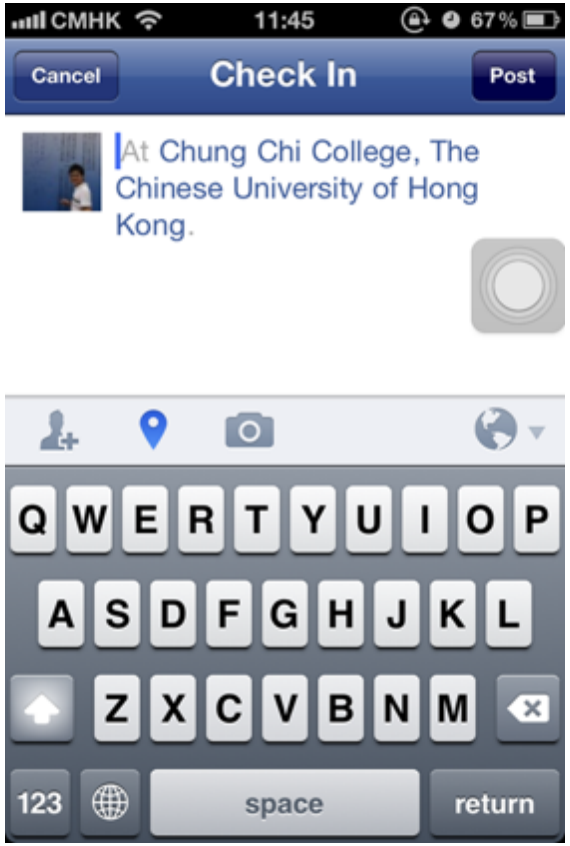
$$
z_{lk} \leftarrow z_{lk} \frac{\sum_{i=1}^{m}(f_{il}^x u_{ik}/x_{il}) + (\alpha_k - 1)/z_{lk}}{\sum_{i=1}^{m} u_{ik} + 1/\beta_k}.
$$

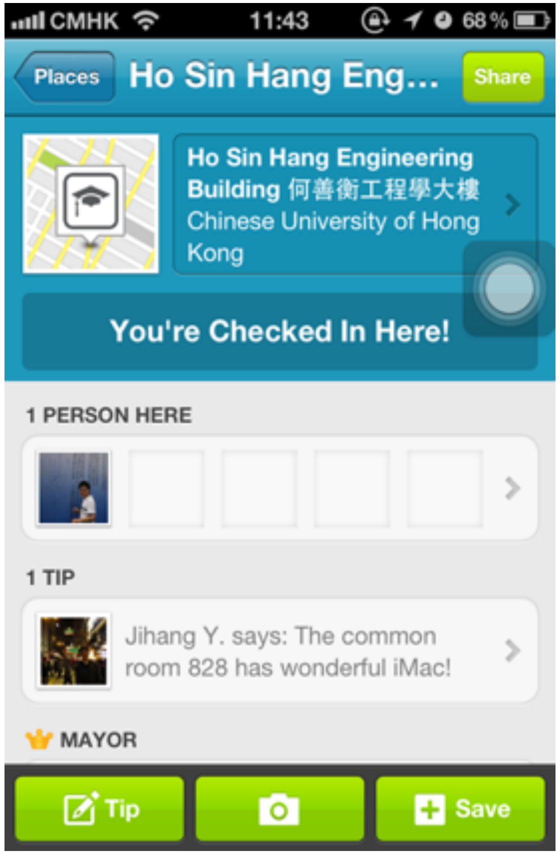
$$
u_{ik} \leftarrow u_{ik} \frac{\theta \sum_{j=1}^{n}(f_{ij}^y v_{jk}/y_{ij}) + (1-\theta) \sum_{l=1}^{p}(f_{il}^x z_{lk}/x_{il}) + (\alpha_k - 1)/u_{ik}}{\theta \sum_{j=1}^{n} v_{jk} + (1-\theta)\sum_{l=1}^{p} z_{lk} + 1/\beta_k}
$$

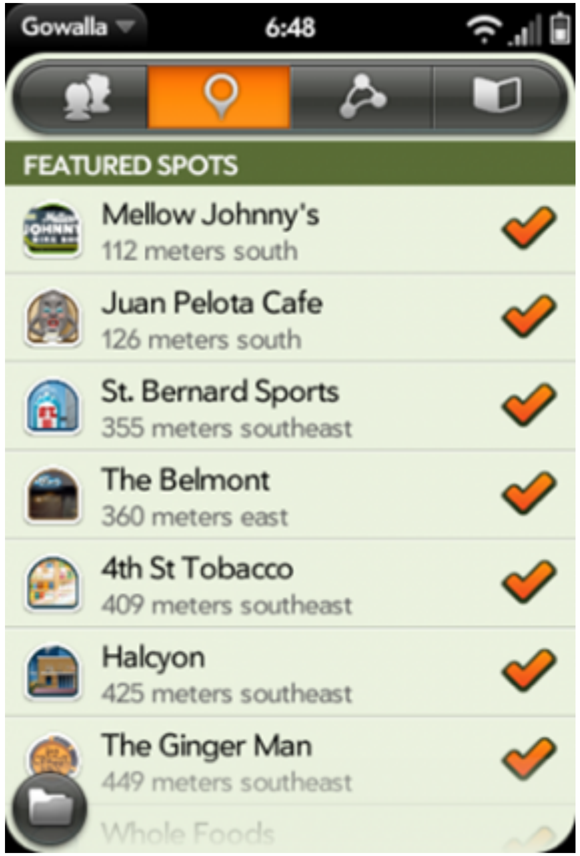
Location Recommendations

[Cheng et al., AAAI 2012]

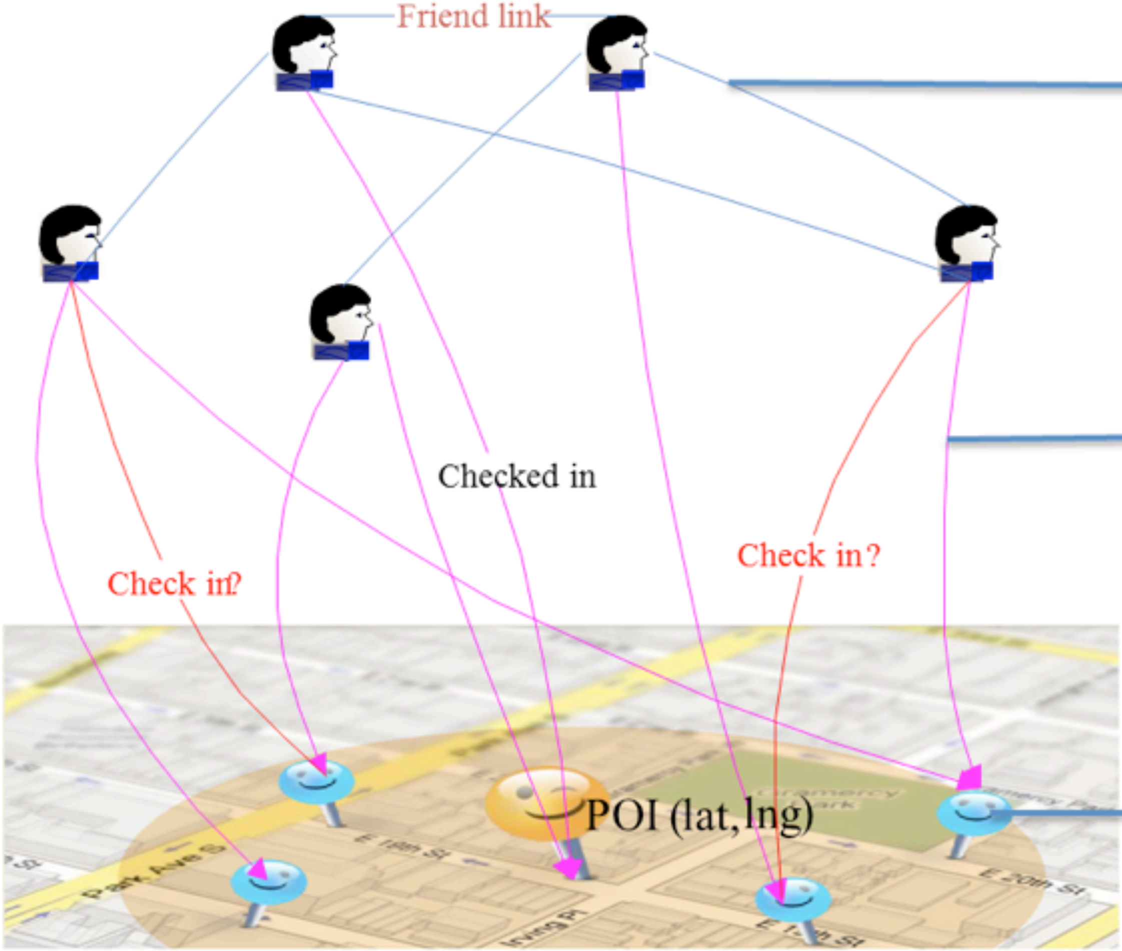
Check Out on "Check-ins"







Location-based Social Networks (LBSNs)



- Community detection
- Link prediction

- POI recommendation
- Next place prediction

- Travel sequence detection
- Trip recommendation

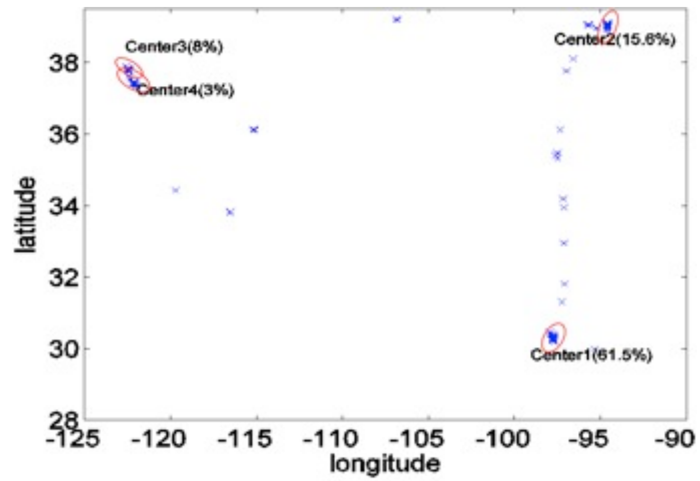
Motivations

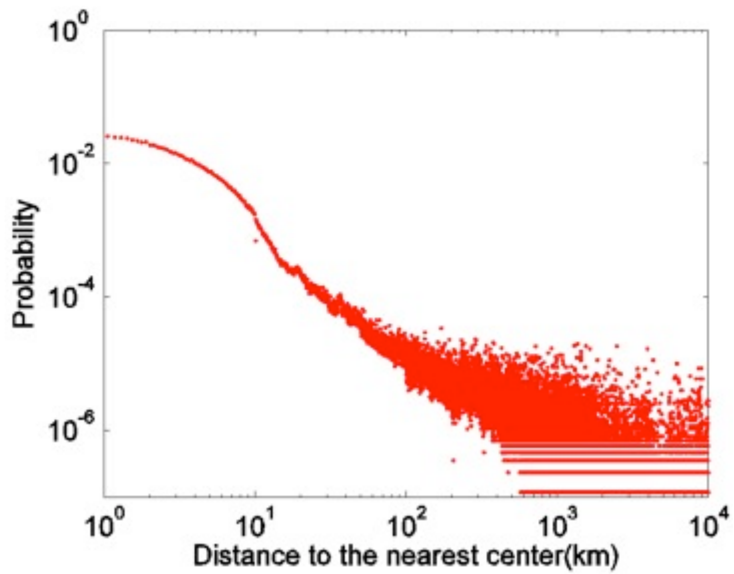
- Users have their personalized taste for different POIs.

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

Observation #1

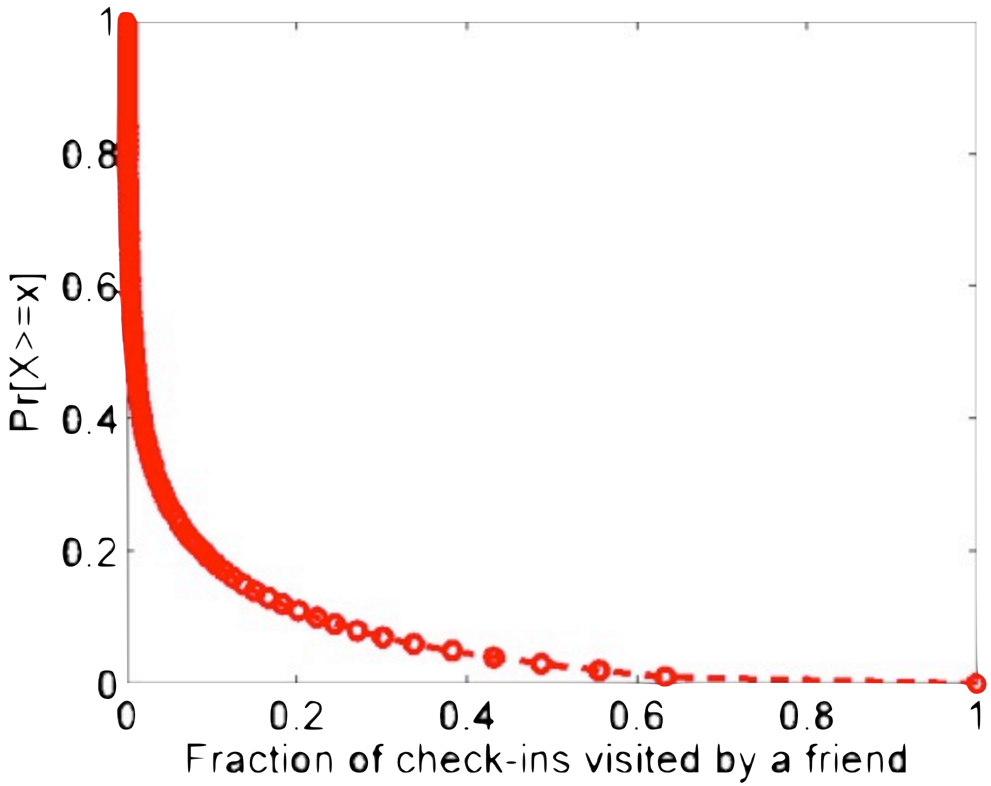
- Users tend to check-in around several centers
- Gaussian distribution to model check-ins at each center
- Inverse Distance Rule: check-in probability is inversely proportional to the distance to the nearest center





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

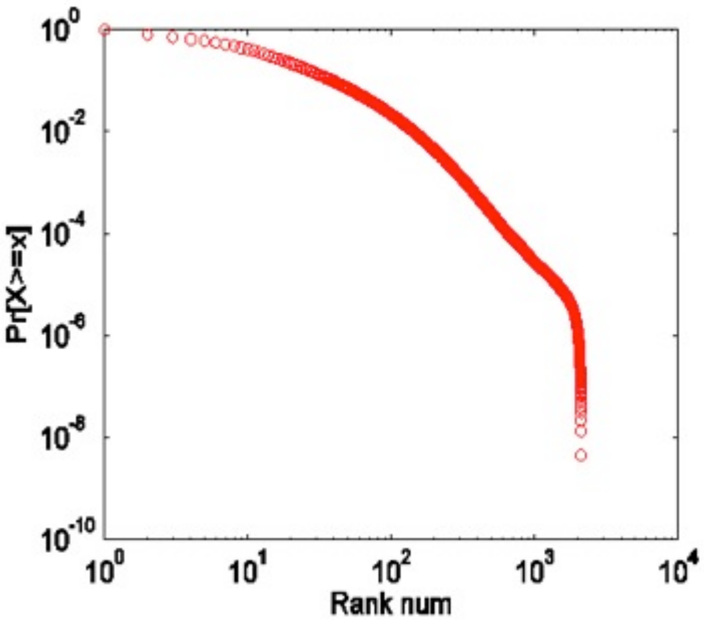
Multi-center Gaussian Model

- 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, 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:

$$P(l|C_u) = \sum_{c_u=1}^{|C_u|} \underbrace{P(l \in c_u)}_{\text{Which center?}} \underbrace{\frac{f_{c_u}^{\alpha}}{\sum_{i \in C_u} f_i^{\alpha}}}_{\text{Frequency normalization}} \underbrace{\frac{\mathcal{N}(l|\mu_{c_u}, \Sigma_{c_u})}{\sum_{i \in C_u} \mathcal{N}(l|\mu_i, \Sigma_i)}}_{\text{Gaussian distribution of the center}}.$$

Multi-center Discovery Algorithm

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




```
for all user i in the user set 𝒰 do
    Rank all check-in locations in |ℒ| according to visiting frequency
    ∀l_k ∈ L, set l_k.center = −1;
    Center_list = ∅; center_no = 0;
    for i = 1 → |L| do
        if l_i.center == −1 then
            center_no++; Center = ∅; Center.total_freq = 0;
            Center.add(l_i); Center.total_freq += l_i.freq;
            for j = i + 1 → |L| do
                if l_j.center == −1 and dist(l_i, l_j) ≤ d then
                    l_j.center = center_no; Center.add(l_j);
                    Center.total_freq += l_j.freq;
                end if
            end for
            if Center.total_freq ≥ |u_i|.total_freq * θ then
                Center_list.add(Center);
            end if
        end if
    end for
    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]:

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

- MGM models **geographical influence**

- We can fuse them together:

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

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 patters, temporal relationships, etc.
- Location recommendation follows a similar path with new data and features.

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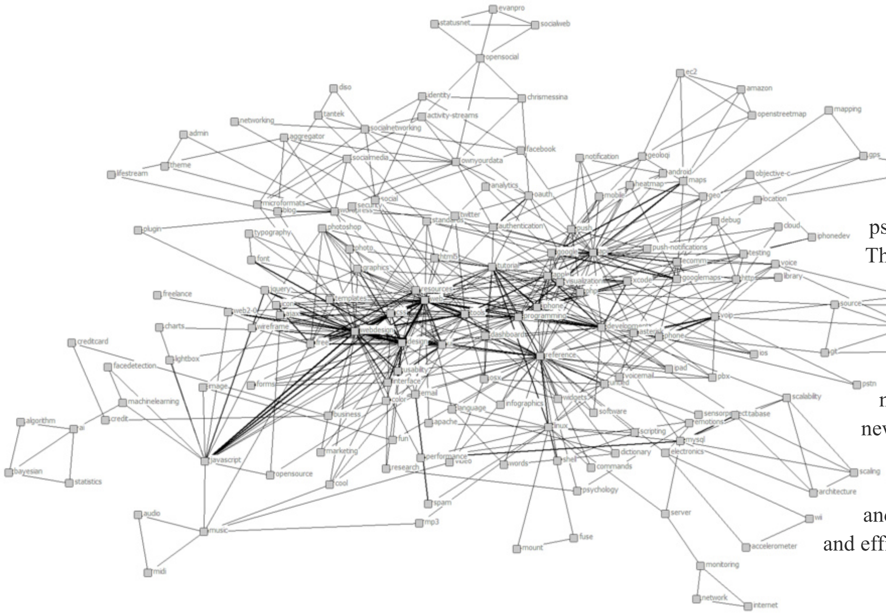

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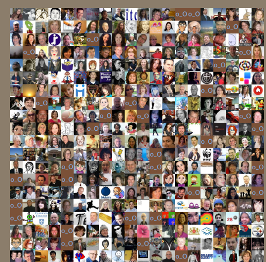

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- Patrick Lau
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On-Going Research

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)

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)

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)

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- A Survey of Human Computation Systems (SCA'09)
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