BEHAVIORAL MODELING IN SOCIAL NETWORKS FROM MICRO TO MACRO

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Outline

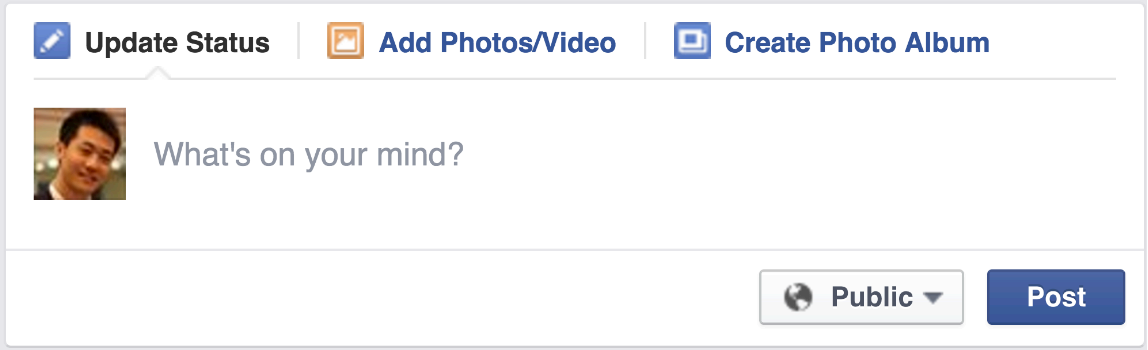
- ❖ **Prediction for natural behavior**
  - ❖ **Modeling individual behavior (MICRO)**
  - ❖ Modeling information cascade (MACRO)
- ❖ Detection for unnatural behavior
  - ❖ Suspicious behavior detection

Questions for Modeling Individual Behavior

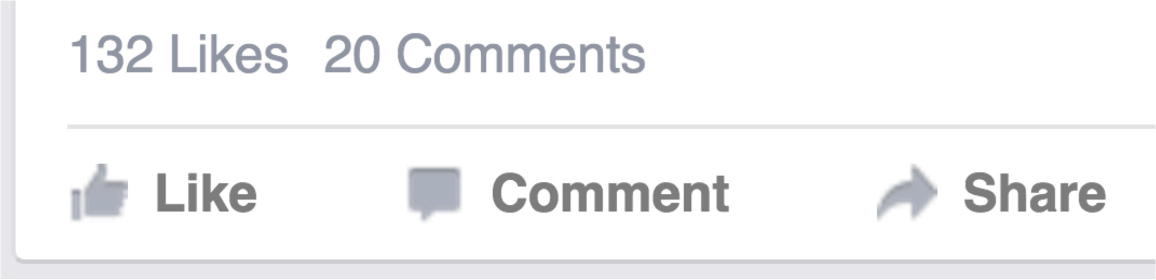
- What is individual behavior in social networks?
- Why should we study individual behavior?
- What are the state-of-the-art models?
  - Modeling behaviors and social relations
  - Modeling social contexts
  - Modeling spatiotemporal contexts
  - Modeling multiple domains in social networks

Individual Behavior: Facebook

- Post: What's on your mind?

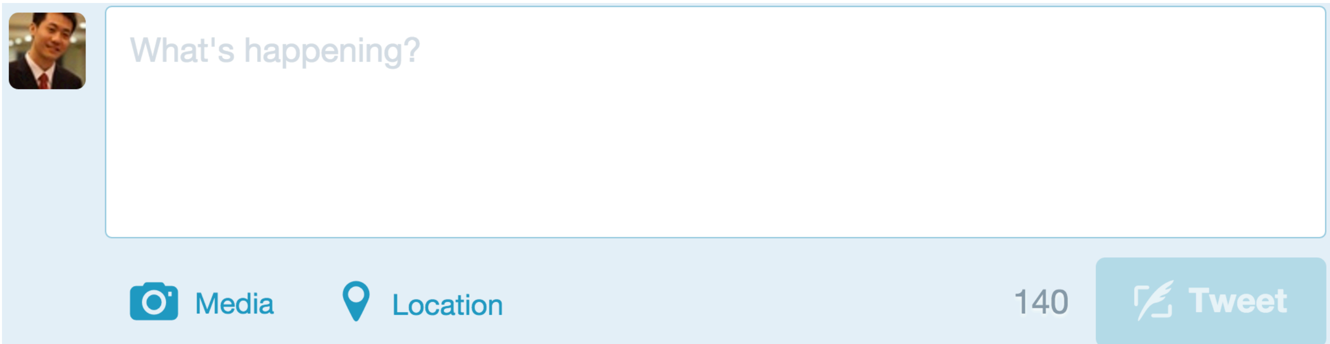


- Like, Comment, Share

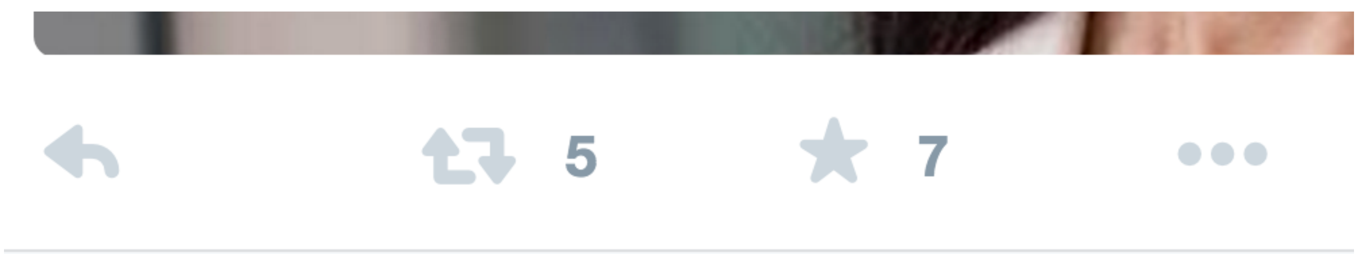


Individual Behavior: Twitter

- Tweet: What’s happening?

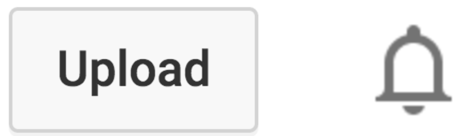


- Reply, Retweet, Favorite

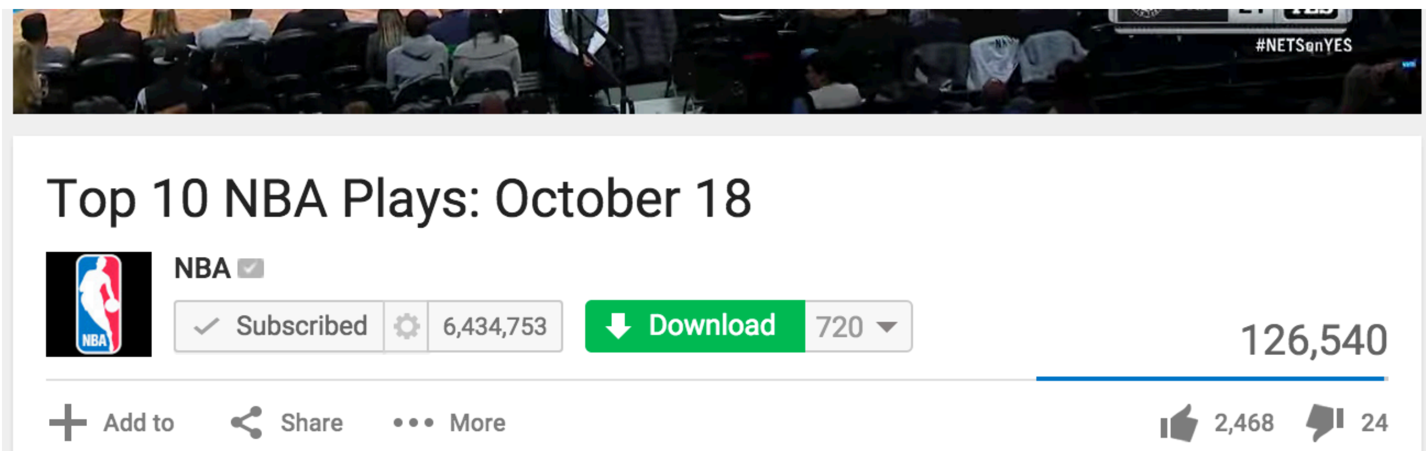


Individual Behavior: YouTube

- Upload

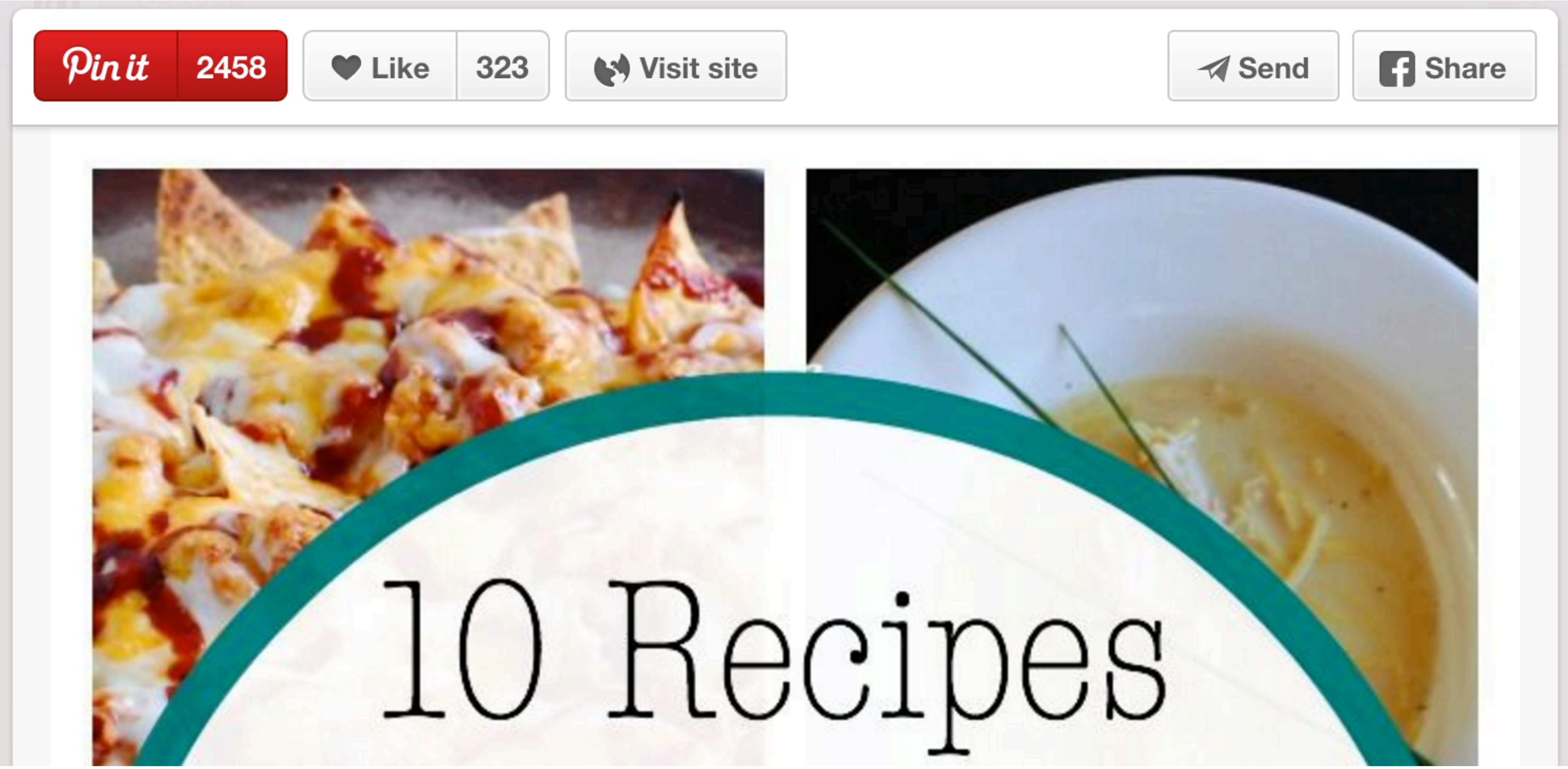


- Subscribe, Download, Add to, Share, Like, Dislike, Comment



Individual Behavior: Pinterest

- Pin it, Like, Visit, Send, Share



"Information Adoption" in Social Networks

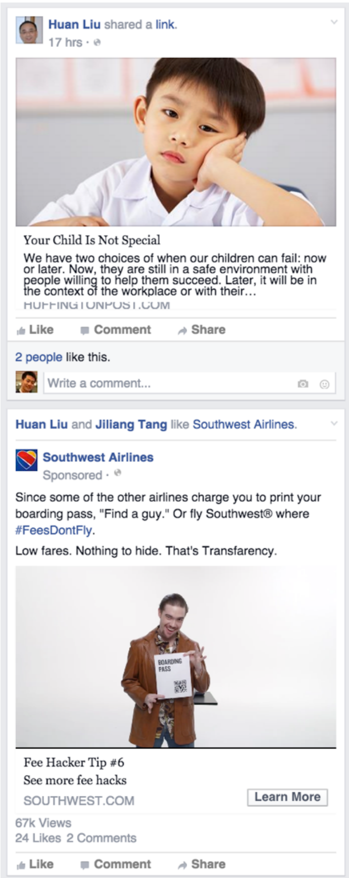
Like
Reply
Share
Favorite
Retweet
Comment
Subscribe
Download
Add to
Send
Pin it
Visit
……

Modeling Information Adoption Behavior

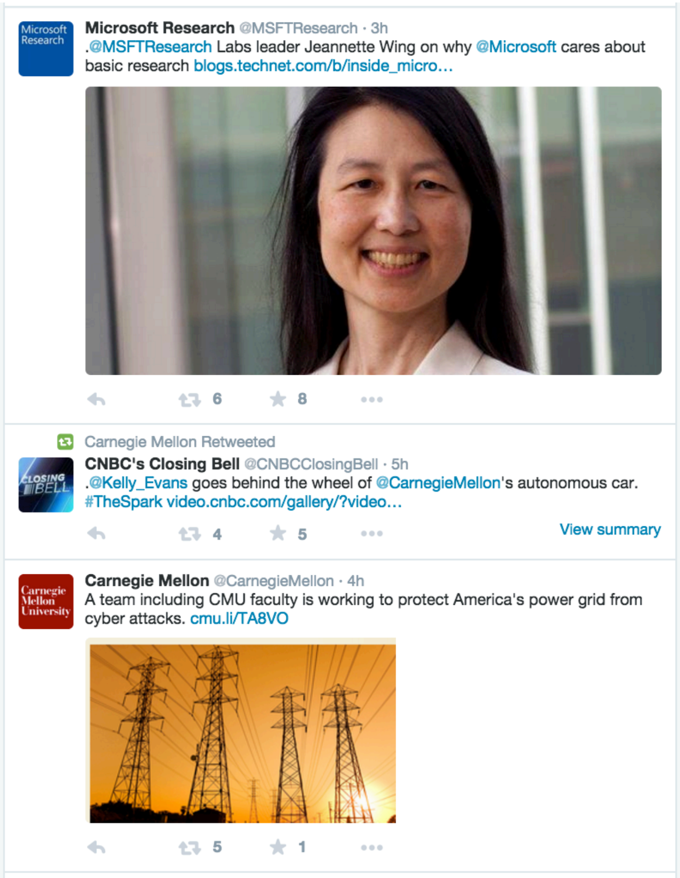
- Behavioral pattern discovery
- Behavior prediction in social networks
- Social recommendation

What is Social Recommendation?

Facebook



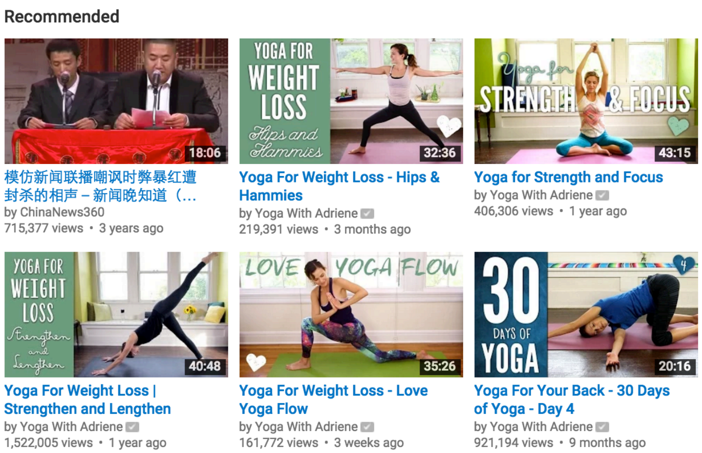
Twitter



News Feed Ranking

What is Social Recommendation?

YouTube



Pinterest

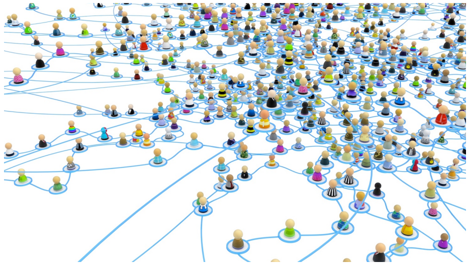
Social Multimedia Recommender Systems

What is Social Recommendation?

- "Social recommendation …, however, it has *no commonly accepted definition*."

What is Social Recommendation?

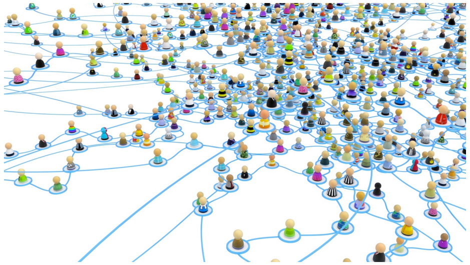
- "Social recommendation …, however, it has *no commonly accepted definition*."
- "A narrow definition of social recommendation is *any recommendation with online social relations as an additional input*, i.e., augmenting an existing recommendation engine with *additional social signals*."



Tang et al. **Social Recommendation: A Review.** *Social Network Analysis and Mining*, 2013. Springer.

What is Social Recommendation?

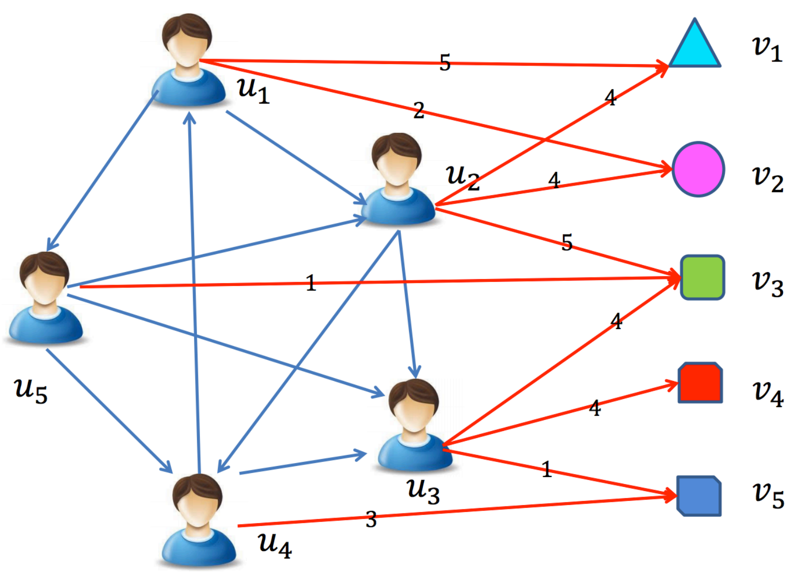
- “Social recommendation …, however, it has *no commonly accepted definition*.”
- “A narrow definition of social recommendation is *any recommendation with online social relations as an additional input*, i.e., augmenting an existing recommendation engine with *additional social signals*.”
- “Users’ preferences are likely to be similar to or influenced by their connected friends. …, social recommendation *leverages user correlations implied social relations* to improve the performance of recommendation.”



Tang et al. **Social Recommendation: A Review.** *Social Network Analysis and Mining*, 2013. Springer.

Traditional Recommender Systems

- Assumed that users are independent and identically distributed



	v_1	v_2	v_3	v_4	v_5
u_1	5	?	2	?	?
u_2	4	4	5	?	?
u_3	?	?	4	4	1
u_4	?	?	?	?	3
u_5	?	?	1	?	?

Traditional Recommender Systems

- Content-based recommender (e.g., TFIDF)
  - For textual information (e.g., news, documents)
  - *Limitation:* limited content analysis, over-specialization

Traditional Recommender Systems

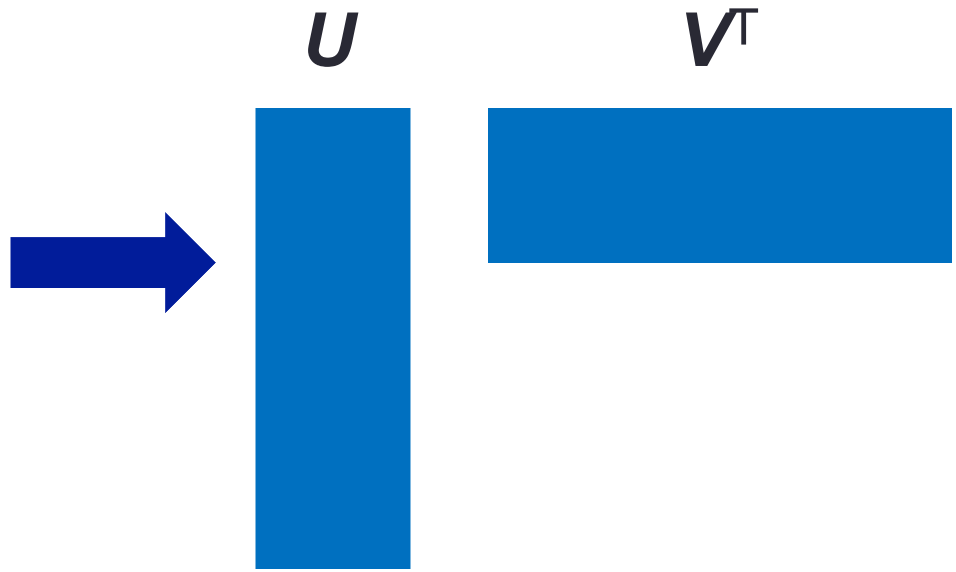
- **Content-based** recommender (e.g., TFIDF)
  - For textual information (e.g., news, documents)
  - *Limitation:* limited content analysis, over-specialization
- **Collaborative filtering** based recommender
  - Memory-based CF (e.g., PCC, similarity)
  - Model-based CF (e.g., factorization based)
  - *Limitation:* data sparsity, cold-start problem
- **Hybrid** recommender system

Matrix Factorization based CF (MF)

- Low-rank MF on the user-item rating matrix ***R***
- User preference vector ***U***
- Item characteristic vector ***V***

R

	v_1	v_2	v_3	v_4	v_5
u_1	5	?	2	?	?
u_2	4	4	5	?	?
u_3	?	?	4	4	1
u_4	?	?	?	?	3
u_5	?	?	1	?	?



Koren. **Factorizatoin Meets the Neighborhood: A Multifaceted Collaborative Filtering Model.** *KDD*, **2008**.

Matrix Factorization based CF (MF)

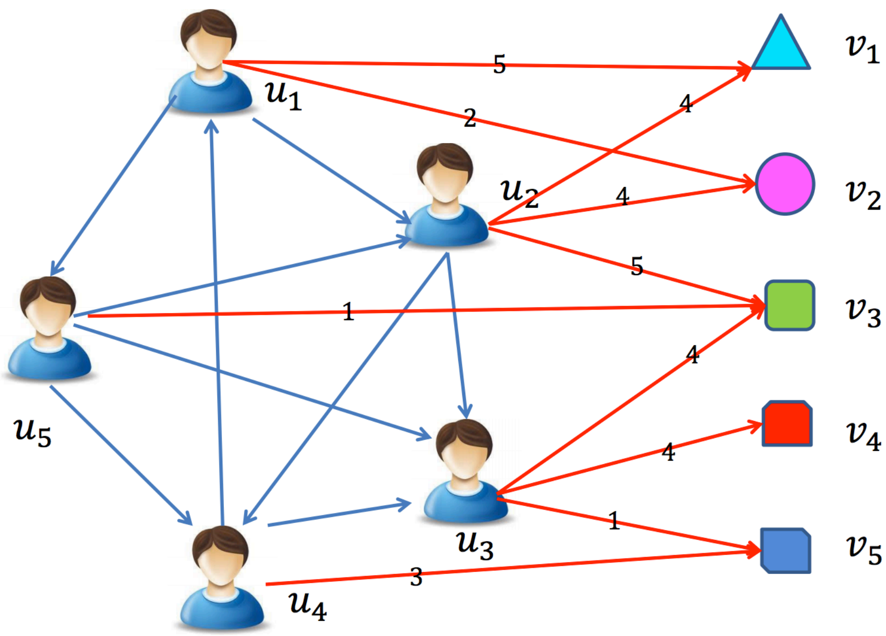
- Low-rank MF on the user-item rating matrix ***R***
- User preference vector ***U***
- Item characteristic vector ***V***
- Observed weight matrix ***W***

$$\min_{\mathbf{U},\mathbf{V}} \sum_{i=1}^{n} \sum_{j=1}^{m} \boxed{\mathbf{W}_{ij}} (\mathbf{R}_{ij} - \mathbf{U}_i \mathbf{V}_j^\top)^2 + \boxed{\alpha(\|\mathbf{U}\|_F^2 + \|\mathbf{V}\|_F^2)}$$

avoid over-fitting,
controlled by the parameter

Social Recommendation

Social relations



	u_1	u_2	u_3	u_4	u_5
u_1	0	1	0	0	1
u_2	0	0	1	1	0
u_3	0	0	0	0	0
u_4	1	0	1	0	0
u_5	0	1	1	1	0

	v_1	v_2	v_3	v_4	v_5
u_1	5	?	2	?	?
u_2	4	4	5	?	?
u_3	?	?	4	4	1
u_4	?	?	?	?	3
u_5	?	?	1	?	?

Tang et al. **Social Recommendation: A Review.** *Social Network Analysis and Mining*, 2013. Springer.

Memory based Social Recommender

- TidalTrust

$$r_{sm} = \frac{\sum_{i \in S} t_{si} r_{im}}{\sum_{i \in S} t_{si}}$$

rating
(user *i*, item *m*)

rating
(user *s*, item *m*)

trust from social relation
(user *s*, user *i*)

Golbeck. **Personalizing applications through integration of inferred trust values in semantic web-based social networks.** *Semantic Network Analysis Workshop*, 2005.

Memory based Social Recommender

- MoleTrust

rating (user u, item i)

average rating (user u)

average rating (user a)

$$p_{a,i} = \bar{r}_a + \frac{\sum_{u=1}^{k} w_{a,u}(r_{u,i} - \bar{r}_u)}{\sum_{u=1}^{k} w_{a,u}}$$

predicted rating (user a, item i)

trust from social relation (user a, user u)

Memory based Social Recommender

- TrustWalker

similarity measure (item *i*, item *j*)

$$P(Y_{u,i} = j) = \frac{sim(i,j)}{\sum_{l \in RI_u} sim(i,l)}$$

probability of user *u*'s random walk from item *i* to item *j*

Pearson correlation of (item *i*, item *j*)

$$sim(i,j) = \frac{1}{1 + e^{-\frac{|UC_{i,j}|}{2}}} \times corr(i,j)$$

common user set of (item *i*, item *j*)

Model based Social Recommender

- Optimization methods such as gradient based methods can be applied to find a well-worked optimal solution.
- MF has a nice probabilistic interpretation with Gaussian noise.
- MF is very flexible and allows us to include prior knowledge.

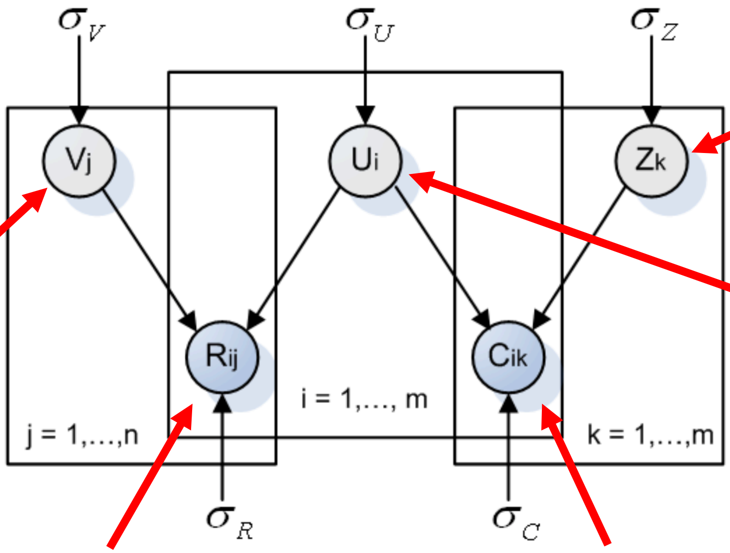
Social Recommendation CF

= *Basic CF* + *Social Information Model*

Tang et al. **Social Recommendation: A Review.** *Social Network Analysis and Mining*, 2013. Springer.

Model based Social Recommender

- SoRec



R: user-item rating matrix

	v_1	v_2	v_3	v_4	v_5
u_1	5	?	2	?	?
u_2	4	4	5	?	?
u_3	?	?	4	4	1
u_4	?	?	?	?	3
u_5	?	?	1	?	?

C: user-user social matrix

	u_1	u_2	u_3	u_4	u_5
u_1	0	1	0	0	1
u_2	0	0	1	1	0
u_3	0	0	0	0	0
u_4	1	0	1	0	0
u_5	0	1	1	1	0

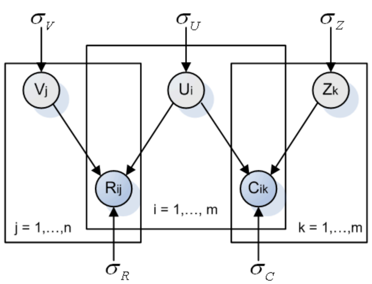
Ma et al. **Social Recommendation Using Probabilistic Matrix Factorization.** *CIKM*, 2008.
Improving Recommender Systems by Incorporating Social Contextual Information. *TIS*, 2011.

Model based Social Recommender

❖SoRec

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

Gaussian distribution



Logistic function Observed

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

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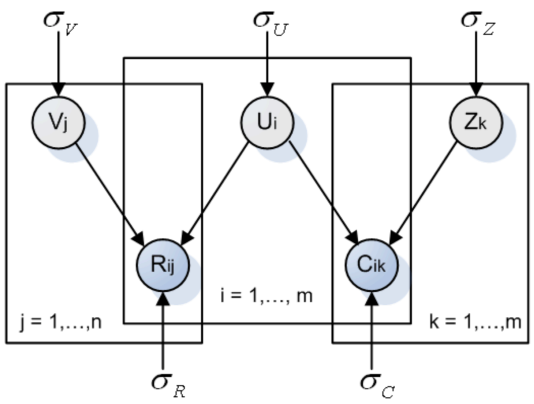
Improving Recommender Systems by Incorporating Social Contextual Information. *TIS*, 2011.

Model based Social Recommender

❖SoRec



behavioral term

social term

$$\mathcal{L}(R, C, U, V, Z) =$$
$$\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}^{R}(r_{ij}-g(U_i^T V_j))^2 + \frac{\lambda_C}{2}\sum_{i=1}^{m}\sum_{k=1}^{m} I_{ik}^{C}(c_{ik}^{*}-g(U_i^T Z_k))^2$$
$$+\frac{\lambda_U}{2}\|U\|_F^2 + \frac{\lambda_V}{2}\|V\|_F^2 + \frac{\lambda_Z}{2}\|Z\|_F^2, \qquad (9)$$

regularization terms

Ma et al. **Social Recommendation Using Probabilistic Matrix Factorization.** *CIKM*, 2008.
Improving Recommender Systems by Incorporating Social Contextual Information. *TIS*, 2011.

Model based Social Recommender

❖SoRec

Gradient Descent Methods

deviate of Logistic function

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

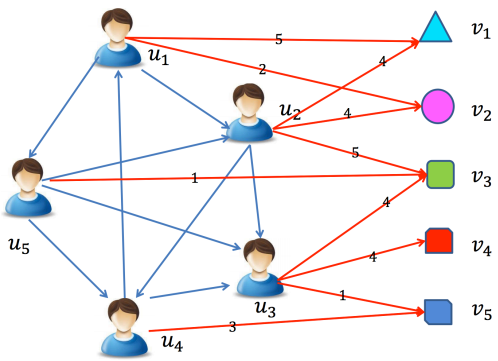
$$\frac{\partial \mathcal{L}}{\partial V_j} = \sum_{i=1}^{m} I_{ij}^{R} \underline{g'(U_i^T V_j)}(g(U_i^T V_j) - r_{ij})U_i + \lambda_V V_j,$$

$$\frac{\partial \mathcal{L}}{\partial Z_k} = \lambda_C \sum_{i=1}^{m} I_{ik}^{C} \underline{g'(U_i^T Z_k)}(g(U_i^T Z_k) - c_{ik}^{*})U_i + \lambda_Z Z_k, (10)$$

Ma et al. **Social Recommendation Using Probabilistic Matrix Factorization.** *CIKM*, 2008.
Improving Recommender Systems by Incorporating Social Contextual Information. *TIS*, 2011.

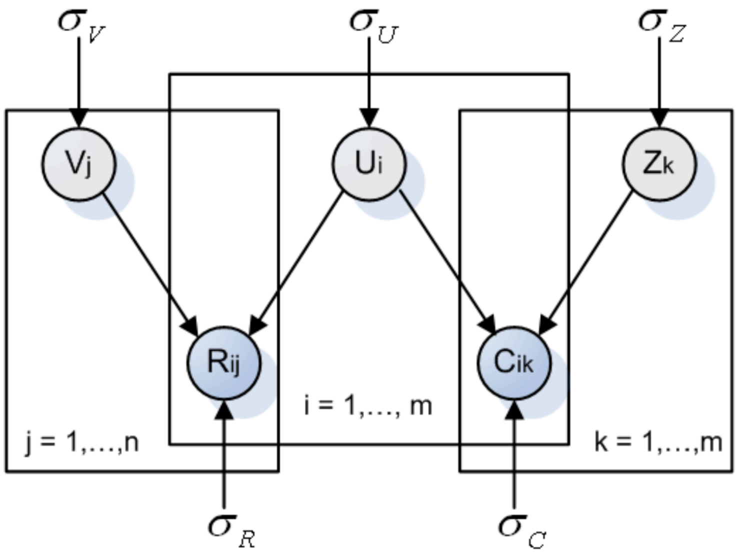
Model based Social Recommender

❖SoRec



	u_1	u_2	u_3	u_4	u_5
u_1	0	1	0	0	1
u_2	0	0	1	1	0
u_3	0	0	0	0	0
u_4	1	0	1	0	0
u_5	0	1	1	1	0

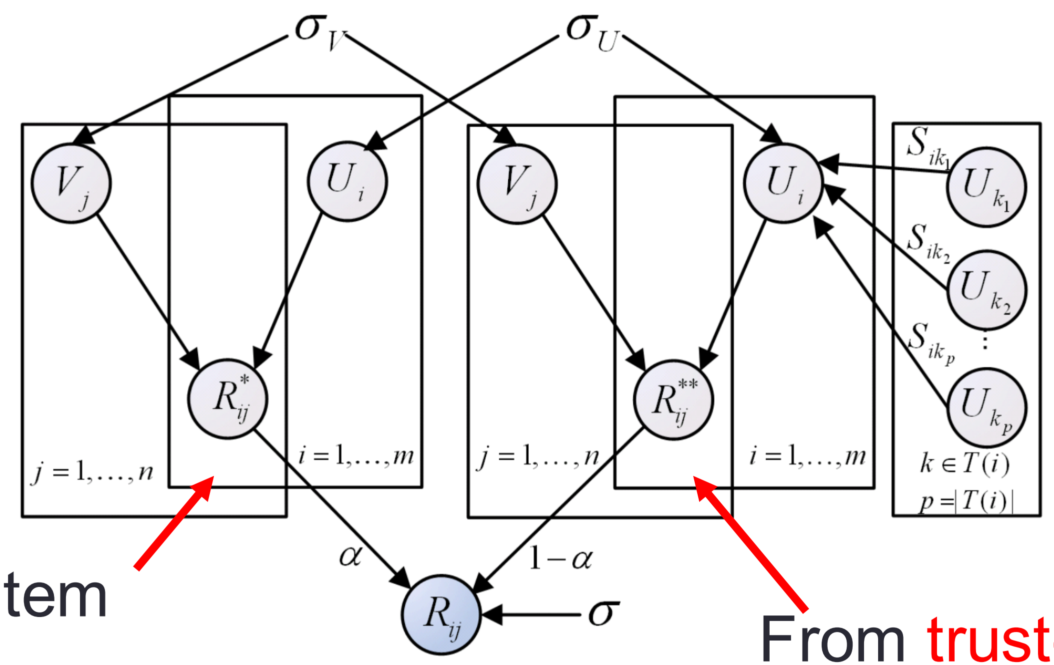
	v_1	v_2	v_3	v_4	v_5
u_1	5	?	2	?	?
u_2	4	4	5	?	?
u_3	?	?	4	4	1
u_4	?	?	?	?	3
u_5	?	?	1	?	?



Ma et al. **Social Recommendation Using Probabilistic Matrix Factorization.** *CIKM*, 2008.
Improving Recommender Systems by Incorporating Social Contextual Information. *TIS*, 2011.

Model based Social Recommender

- ❖Replacing social with trust
- ❖"Social Trust" Ensemble for Epinion data



From user-item matrix

From trusted friends

Operation "plus"

Model based Social Recommender

- "Social Trust" Ensemble

From user-item matrix

From trusted friends

$$\mathcal{L}(R,S,U,V) = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}^{R}\Big(R_{ij} - g\big(\underline{\alpha U_i^T V_j} + \underline{(1-\alpha)\sum_{k\in\mathcal{T}(i)} S_{ik}U_k^T V_j}\big)\Big)^2 + \frac{\lambda_U}{2}\|U\|_F^2 + \frac{\lambda_V}{2}\|V\|_F^2, \quad (13)$$

Model based Social Recommender

- "Social Trust" Ensemble

Gradient Descent Methods

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

$$\frac{\partial \mathcal{L}}{\partial V_j} = \sum_{i=1}^{m} I_{ij}^R g'(\alpha U_i^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T V_j)$$
$$\times (g(\alpha U_i^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T V_j) - R_{ij})$$
$$\times (\alpha U_i + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T) + \lambda_V V_j, \qquad (14)$$

Ma et al. **Learning to Recommend with Social Trust Ensemble.** *SIGIR*, 2009.
Learning to Recommend with Explicit and Implicit Social Relations. *TIST*, 2011.

Model based Social Recommender

- SoReg

Average-based regularization:
Regularize with the average of friends' tastes

$$\min_{U,V} \mathcal{L}_1(R,U,V) = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}(R_{ij} - U_i^T V_j)^2$$
$$\boxed{+ \frac{\alpha}{2}\sum_{i=1}^{m} \|U_i - \frac{\sum_{f\in\mathcal{F}^+(i)} Sim(i,f)\times U_f}{\sum_{f\in\mathcal{F}^+(i)} Sim(i,f)}\|_F^2,}$$
$$+ \frac{\lambda_1}{2}\|U\|_F^2 + \frac{\lambda_2}{2}\|V\|_F^2. \qquad (8)$$

Information loss: Friends may have diverse tastes!!!

Model based Social Recommender

❖SoReg

Individual-based regularization:
Regularize with friends individually

$$
\begin{aligned}
\min_{U,V} \mathcal{L}_2(R,U,V) &= \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}(R_{ij} - U_i^T V_j)^2 \\
&\boxed{+ \quad \frac{\beta}{2}\sum_{i=1}^{m}\sum_{f\in\mathcal{F}^+(i)} Sim(i,f)\|U_i - U_f\|_F^2} \\
&+ \quad \lambda_1\|U\|_F^2 + \lambda_2\|V\|_F^2. \qquad (11)
\end{aligned}
$$

Social Recommenders Before 2012

	Behavior	Social	Trust
SoRec [CIKM'08, TIS'11]	√	√	
"Social Trust" Ensemble [SIGIR'09, TIST'11]	√		√
SoReg [WSDM'11]	√	√	

$\underbrace{\hspace{6cm}}$

Social Contextual Information

Jiang et al. **Social Contextual Recommendation.** *CIKM*, 2012. **Social Recommendation with Contextual Information.** *TKDE,* 2014.

Social Contextual Information

❖ Twitter

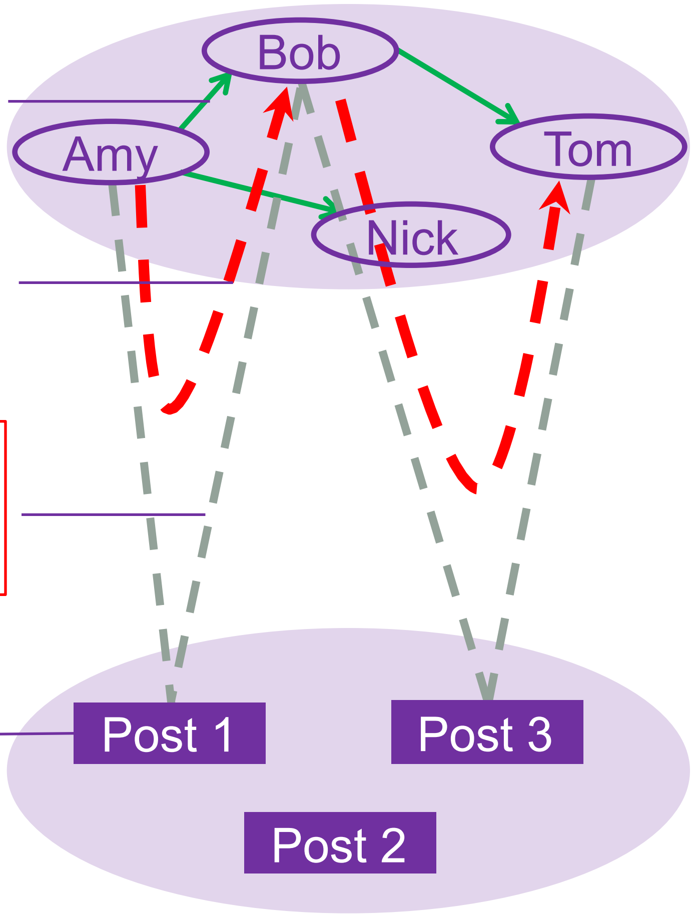
social relation = social

interaction frequency ≈ trust

retweeting/ rating = behavior

Additional signals

item content



Jiang et al. **Social Contextual Recommendation.** *CIKM*, 2012. **Social Recommendation with Contextual Information.** *TKDE,* 2014.

Behavioral **Mechanism?**

(0) follow

Jiang et al. **Social Contextual Recommendation.** *CIKM*, 2012. **Social Recommendation with Contextual Information.** *TKDE,* 2014.

Information Adoption Behavior **Intention**

(0) follow

(2) receive & read

(1) post

Information Adoption Behavior **Intention**

Jiang et al. **Social Contextual Recommendation.** *CIKM*, 2012. **Social Recommendation with Contextual Information.** *TKDE,* 2014.

Information Adoption Behavior **Intention**

Birthday –
NOT politic issues!

(0) follow

(2) receive & read

(1) post

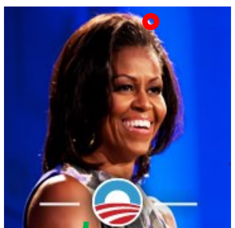
(3) adopt?

Jiang et al. **Social Contextual Recommendation.** *CIKM*, 2012. **Social Recommendation with Contextual Information.** *TKDE*, 2014.

Information Adoption Behavior **Intention**

Birthday –
NOT politic issues!

From my husband –
NOT fans on Twitter!



(0) follow

(2) receive & read

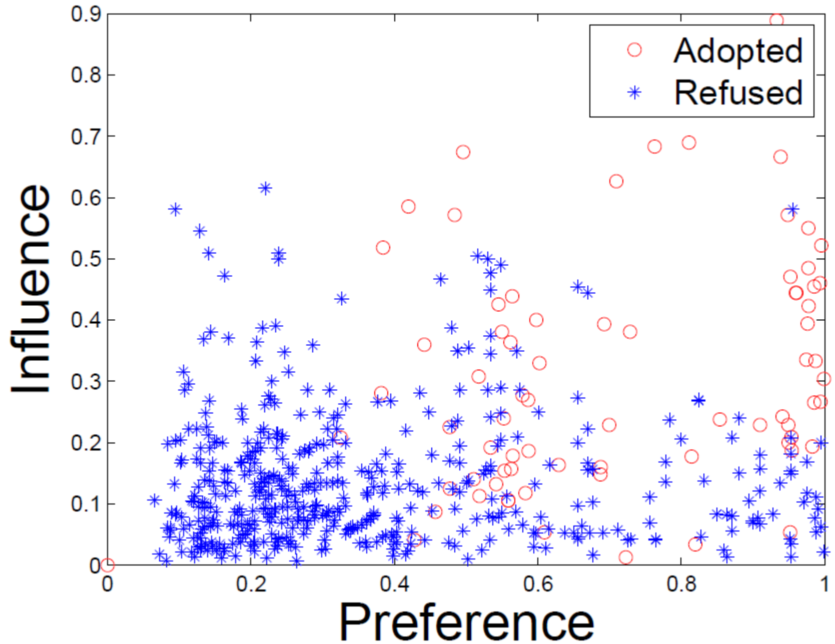
(1) post

(3) adopt?

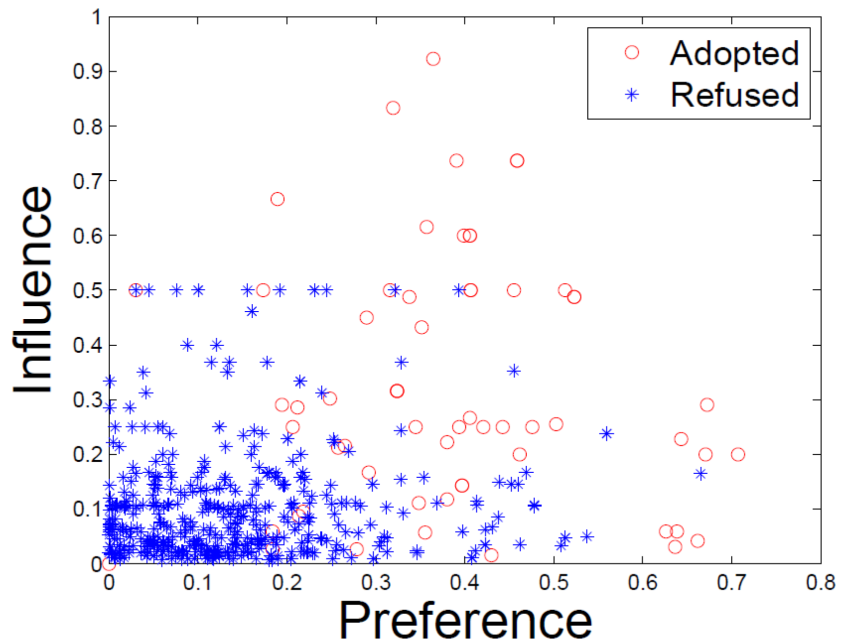
Jiang et al. **Social Contextual Recommendation.** *CIKM*, 2012. **Social Recommendation with Contextual Information.** *TKDE*, 2014.

Social Contextual Factors

❖Individual Preference & Interpersonal Influence



China's Facebook:
Renren



China's Twitter:
Tencent Weibo

Jiang et al. **Social Contextual Recommendation.** *CIKM*, 2012. **Social Recommendation with Contextual Information.** *TKDE,* 2014.

From *Information* to *Factors*

Content:

item content

Behavior:

user-item interaction

Social:

social relation

Trust/interaction:

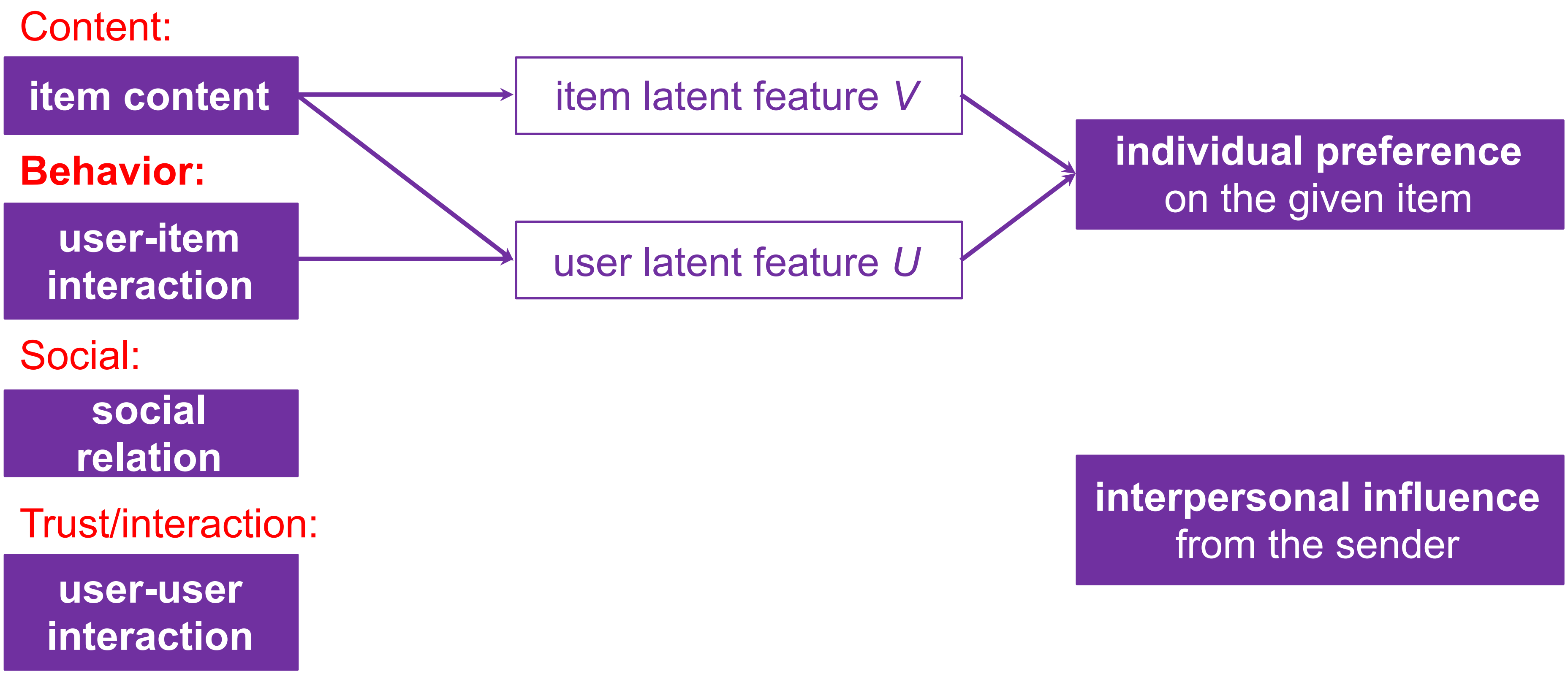
user-user interaction

individual preference on the given item

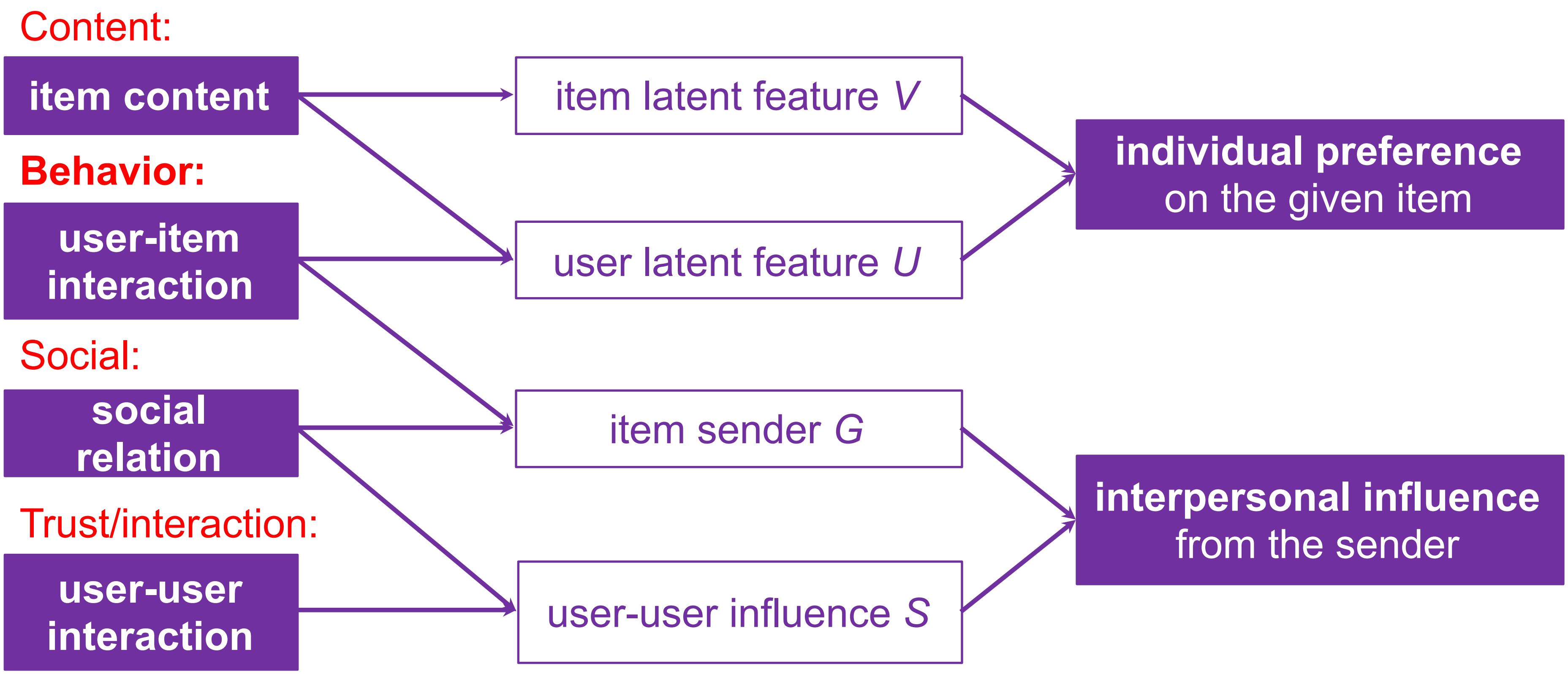
interpersonal influence from the sender

Jiang et al. **Social Contextual Recommendation.** *CIKM*, 2012. **Social Recommendation with Contextual Information.** *TKDE*, 2014.

From *Information* to *Factors*



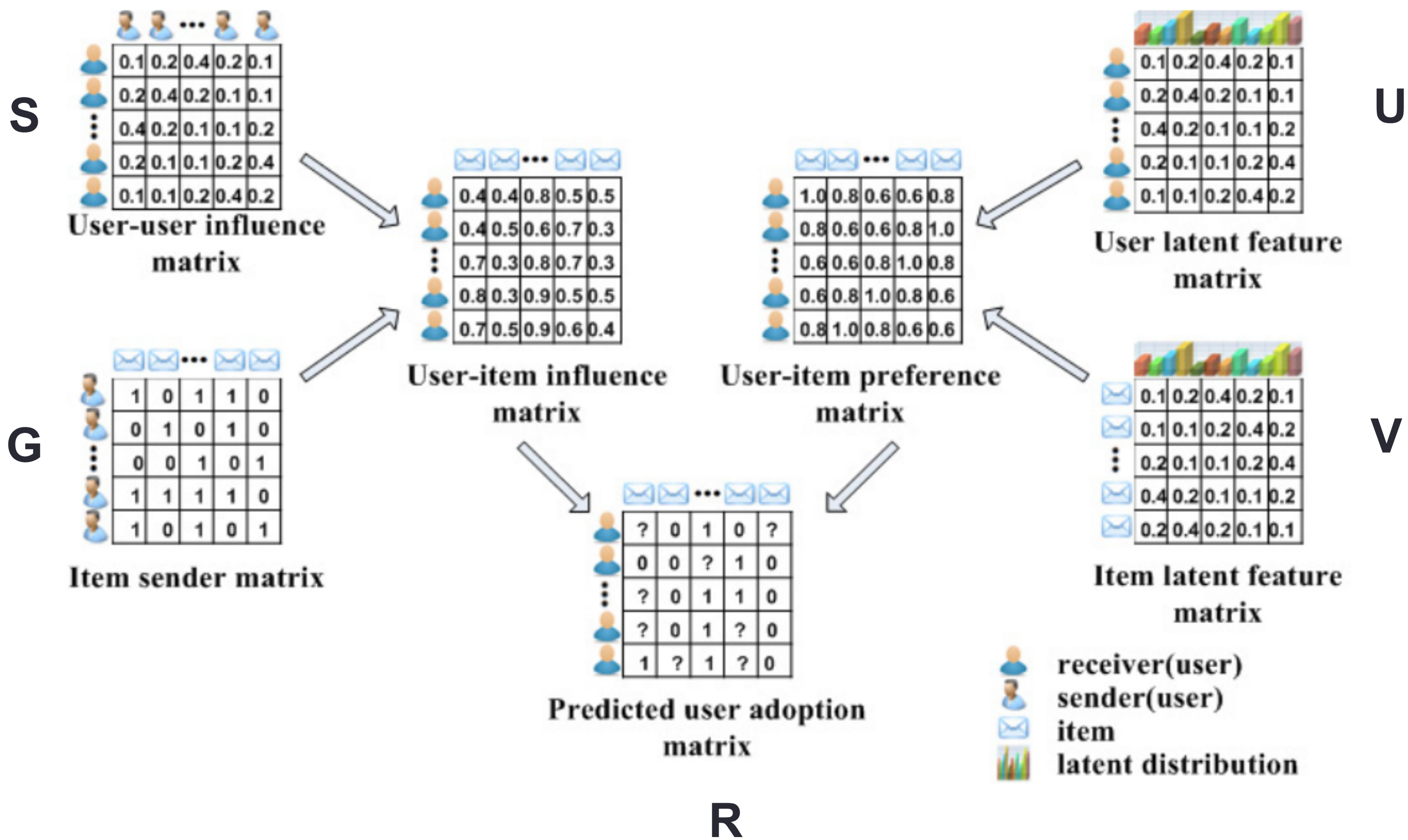
From *Information* to *Factors*



Jiang et al. **Social Contextual Recommendation.** *CIKM*, 2012. **Social Recommendation with Contextual Information.** *TKDE,* 2014.

Social Contextual Recommendation

- ContextMF



Jiang et al. **Social Contextual Recommendation.** *CIKM*, 2012. **Social Recommendation with Contextual Information.** *TKDE*, 2014.

Social Contextual Recommendation

- ContextMF

behavior influence preference

$$P(\mathbf{R}|\mathbf{S},\mathbf{U},\mathbf{V},\sigma_R^2) = \prod_{i=1}^{M}\prod_{j=1}^{N}\mathcal{N}(\underline{\mathbf{R}_{ij}}|\underline{\mathbf{S}_i\mathbf{G}_j^\top} \odot \underline{\mathbf{U}_i^\top\mathbf{V}_j},\sigma_R^2)$$

behavior interaction frequency/trust

item content

$$\mathcal{J} = ||\underline{\mathbf{R} - \mathbf{S}\mathbf{G}^\top \odot \mathbf{U}^\top\mathbf{V}}||_F^2 + \alpha||\underline{\mathbf{W} - \mathbf{U}^\top\mathbf{U}}||_F^2$$
$$+\beta||\underline{\mathbf{C} - \mathbf{V}^\top\mathbf{V}}||_F^2 + \gamma||\underline{\mathbf{S} - \mathbf{F}}||_F^2$$
$$+\delta||\mathbf{S}||_F^2 + \eta||\mathbf{U}||_F^2 + \lambda||\mathbf{V}||_F^2$$

social relation

Jiang et al. **Social Contextual Recommendation.** *CIKM*, 2012. **Social Recommendation with Contextual Information.** *TKDE,* 2014.

Social Contextual Recommendation

❖ContextMF

Gradient Descent Methods

$$\frac{\partial \mathcal{J}}{\partial \mathbf{S}} = 2\Big(-\mathbf{R}(\mathbf{G} \odot \mathbf{V}^\top \mathbf{U}) + (\mathbf{S}\mathbf{G}^\top \odot \mathbf{U}^\top \mathbf{V})\mathbf{G} + \gamma(\mathbf{S} - \mathbf{F}) + \delta\mathbf{S}\Big)$$

$$\frac{\partial \mathcal{J}}{\partial \mathbf{U}} = 2\Big(-\mathbf{V}\mathbf{R}^\top + \mathbf{V}(\mathbf{G}\mathbf{S}^\top \odot \mathbf{V}^\top \mathbf{U}) - 2\alpha\mathbf{U}\mathbf{W} + 2\alpha\mathbf{U}\mathbf{U}^\top\mathbf{U} + \eta\mathbf{U}\Big)$$

$$\frac{\partial \mathcal{J}}{\partial \mathbf{V}} = 2\Big(-\mathbf{U}\mathbf{R} + \mathbf{U}(\mathbf{S}\mathbf{G}^\top \odot \mathbf{U}^\top \mathbf{V}) - 2\beta\mathbf{V}\mathbf{C} + 2\beta\mathbf{V}\mathbf{V}^\top\mathbf{V} + \lambda\mathbf{V}\Big)$$

Jiang et al. **Social Contextual Recommendation.** *CIKM*, 2012. **Social Recommendation with Contextual Information.** *TKDE,* 2014.

Social Contextual Recommendation

- ContextMF

	Renren	Tencent Weibo
MAE	-19.1%	-24.2%
RMSE	-12.8%	-20.7%
Kendall's	+9.82%	+2.1%
Spearman's	+10.6%	+3.1%

Method	MAE	RMSE	$\hat{\tau}$	$\hat{\rho}$
Renren Dataset				
Content-based [1]	0.3842	0.4769	0.5409	0.5404
Item CF [25]	0.3601	0.4513	0.5896	0.5988
FeedbackTrust [22]	0.3764	0.4684	0.5433	0.5469
Influence-based [9]	0.3859	0.4686	0.5394	0.5446
SoRec [19]	0.3276	0.4127	0.6168	0.6204
SoReg [20]	0.2985	0.3537	0.7086	0.7140
Influence MF	0.3102	0.3771	0.6861	0.7006
Preference MF	0.3032	0.3762	0.6937	0.7036
Context MF	**0.2416**	**0.3086**	**0.7782**	**0.7896**
Tencent Weibo Dataset				
Content-based [1]	0.2576	0.3643	0.7728	0.7777
Item CF [25]	0.2375	0.3372	0.7867	0.8049
FeedbackTrust [22]	0.2830	0.3887	0.7094	0.7115
Influence-based [9]	0.2651	0.3813	0.7163	0.7275
SoRec [19]	0.2256	0.3325	0.7973	0.8064
SoReg [20]	0.1997	0.2962	0.8390	0.8423
Influence MF	0.2183	0.3206	0.8179	0.8258
Preference MF	0.2111	0.3088	0.8384	0.8453
Context MF	**0.1514**	**0.2348**	**0.8570**	**0.8685**

Jiang et al. **Social Contextual Recommendation.** *CIKM*, 2012. **Social Recommendation with Contextual Information.** *TKDE,* 2014.

Co-Predicting Behavior and Social Relations

- LOCABAL

behavior

social relation

$$\mathcal{J} = \|\boxed{\mathbf{W} \odot} (\mathbf{R} - \mathbf{U}^\top \mathbf{V})\|_F^2 + \alpha \|\boxed{\mathbf{T} \odot} (\mathbf{S} - \mathbf{U}^\top \mathbf{H} \mathbf{U})\|_F^2 + \lambda(\|\mathbf{U}\|_F^2 + \|\mathbf{V}\|_F^2 + \|\mathbf{H}\|_F^2) \quad (10)$$

Observed behavioral data

Observed social relation data

Co-Predicting Behavior and Social Relations

❖LOCABAL

Gradient Descent *Methods*

$$\begin{aligned}
\frac{\partial \mathcal{J}}{\partial \mathbf{U}} &= 2\big(-\mathbf{V}(\mathbf{W} \odot \mathbf{W} \odot \mathbf{R})^\top + \mathbf{V}(\mathbf{W} \odot \mathbf{W} \odot (\mathbf{U}^\top \mathbf{V}))^\top \\
&\quad - \alpha \mathbf{H}^\top \mathbf{U}(\mathbf{T} \odot \mathbf{S}) - \alpha \mathbf{H}\mathbf{U}(\mathbf{T} \odot \mathbf{S})^\top + \lambda \mathbf{U} \\
&\quad + \alpha \mathbf{H}^\top \mathbf{U}(\mathbf{T} \odot (\mathbf{U}^\top \mathbf{H}\mathbf{U})) + \alpha \mathbf{H}\mathbf{U}(\mathbf{T} \odot (\mathbf{U}^\top \mathbf{H}\mathbf{U}))^\top \big), \\
\frac{\partial \mathcal{J}}{\partial \mathbf{V}} &= 2\big(-\mathbf{U}(\mathbf{W} \odot \mathbf{W} \odot \mathbf{R}) \\
&\quad + \mathbf{U}(\mathbf{W} \odot \mathbf{W} \odot (\mathbf{U}^\top \mathbf{V})) + \lambda \mathbf{V} \big), \\
\frac{\partial \mathcal{J}}{\partial \mathbf{H}} &= 2\big(-\lambda \mathbf{U}(\mathbf{T} \odot \mathbf{S})\mathbf{U}^\top \\
&\quad + \alpha \mathbf{U}(\mathbf{T} \odot (\mathbf{U}^\top \mathbf{H}\mathbf{U}))\mathbf{U}^\top + \lambda \mathbf{H}\big) \qquad (11)
\end{aligned}$$

Co-Predicting Behavior and Social Relations

❖LOCABAL

Datasets	Training Set	Metrics	Algorithms			
			MF	**SoRec**	**SoReg**	LOCABAL
Ciao	50%	MAE	0.9927	0.9619	0.9552	0.9356
		RMSE	1.1742	1.1375	1.1291	1.1088
	70%	MAE	0.9715	0.9446	0.9328	0.9234
		RMSE	1.1478	1.1140	1.1097	1.0861
	90%	MAE	0.9614	0.9433	0.9232	0.9076
		RMSE	1.1384	1.1028	1.0999	1.0758
Epinions	50%	MAE	0.9935	0.9574	0.9383	0.9237
		RMSE	1.1922	1.1581	1.1479	1.1276
	70%	MAE	0.9701	0.9480	0.9296	0.9088
		RMSE	1.1833	1.1482	1.1277	1.1079
	90%	MAE	0.9687	0.9397	0.9188	0.8981
		RMSE	1.1791	1.1387	1.1170	1.1000

Tang et al. **Exploiting Local and Global Social Context for Recommendation.** *IJCAI*, 2013.

Negative Experiences in Social Recommender

- Data sparsity problem: sparse matrix.
- Social relation are too noisy and may have a negative impact on recommender systems.
- It is difficult for social recommenders to improve recommendation performance for cold-start users.
- Different types of social relations have different effects on social recommender systems.

Tang et al. **Social Recommendation: A Review.** *Social Network Analysis and Mining*, 2013. Springer.

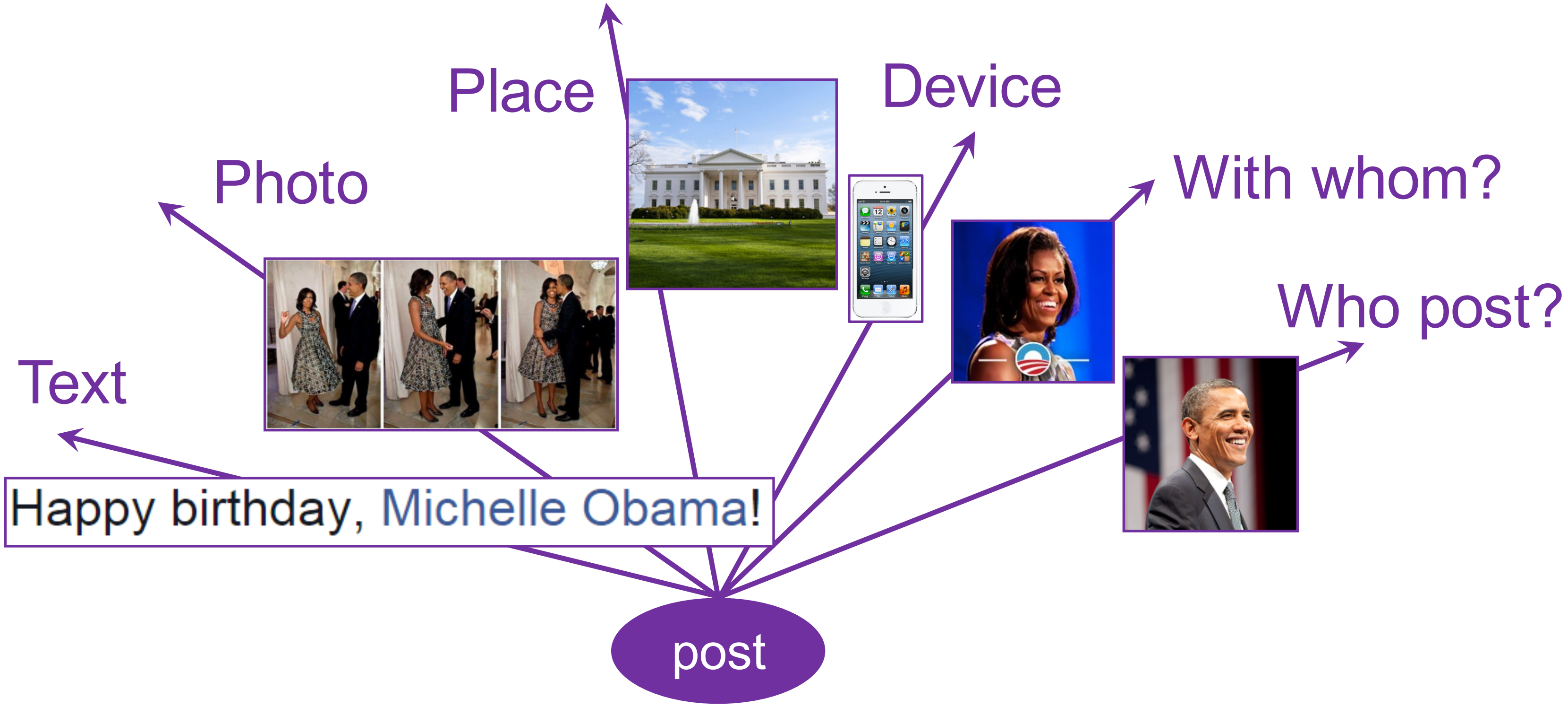
Negative Experiences in Social Recommender

- Data sparsity problem: sparse matrix.
- Social relation are too noisy and may have a negative impact on recommender systems.
- It is difficult for social recommenders to improve recommendation performance for cold-start users.
- Different types of social relations have different effects on social recommender systems.

Future work?
Data integration and causal analysis

Tang et al. **Social Recommendation: A Review.** *Social Network Analysis and Mining*, 2013. Springer.

Besides Social Context: Spatial Context



Jiang et al. **Flexible Evolutionary Multi-faceted Analysis for Dynamic Behavioral Pattern Discovery.** *KDD*, 2014.

Besides Social Context: Temporal Context

Photo

Text

Happy birthday, Michelle Obama!

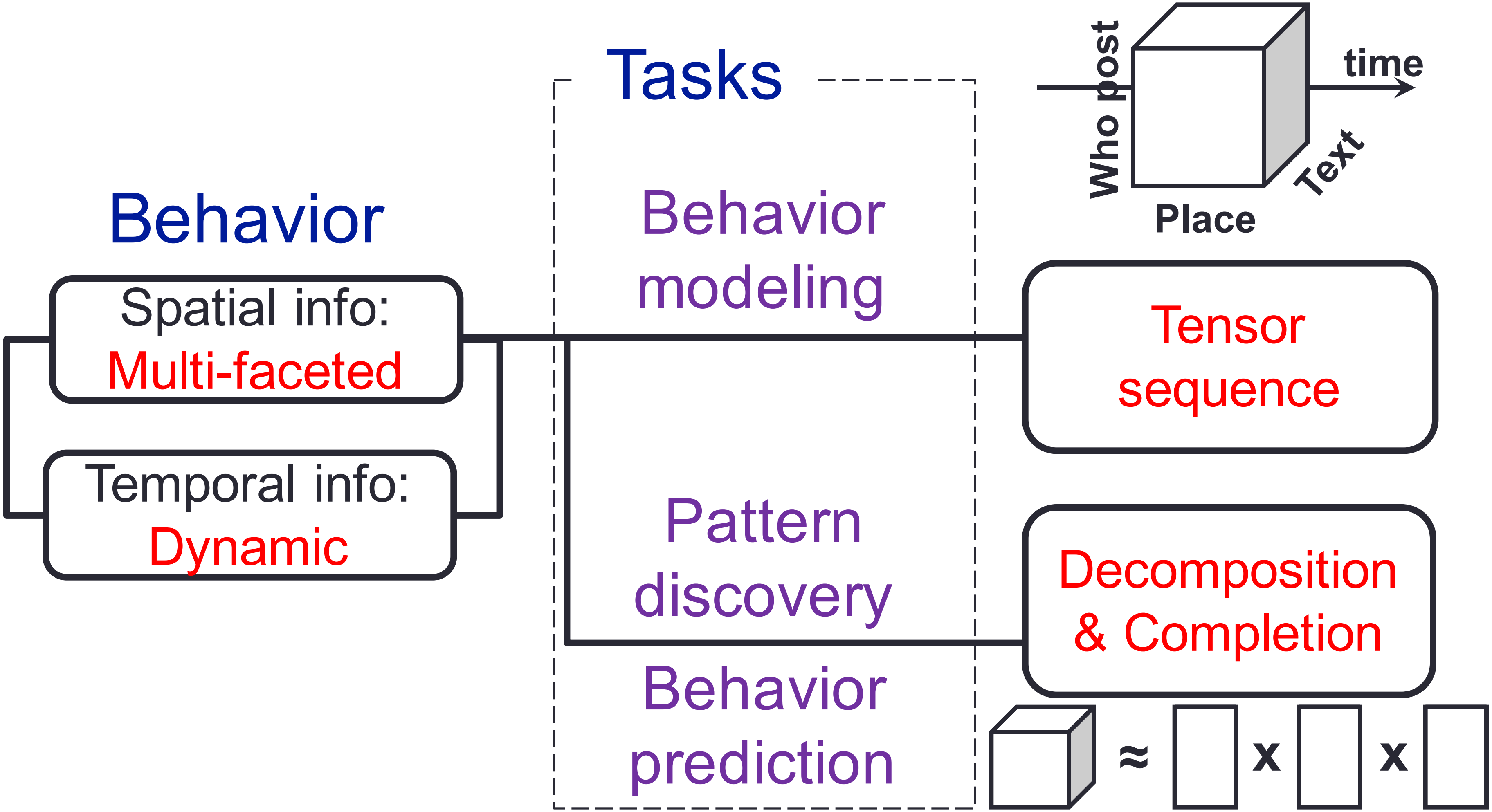
post → post → time

Jan. 18
Birthday party
@ White house

March 17
St. Patrick's Day
@ Bar

Jiang et al. **Flexible Evolutionary Multi-faceted Analysis for Dynamic Behavioral Pattern Discovery.** *KDD*, 2014.

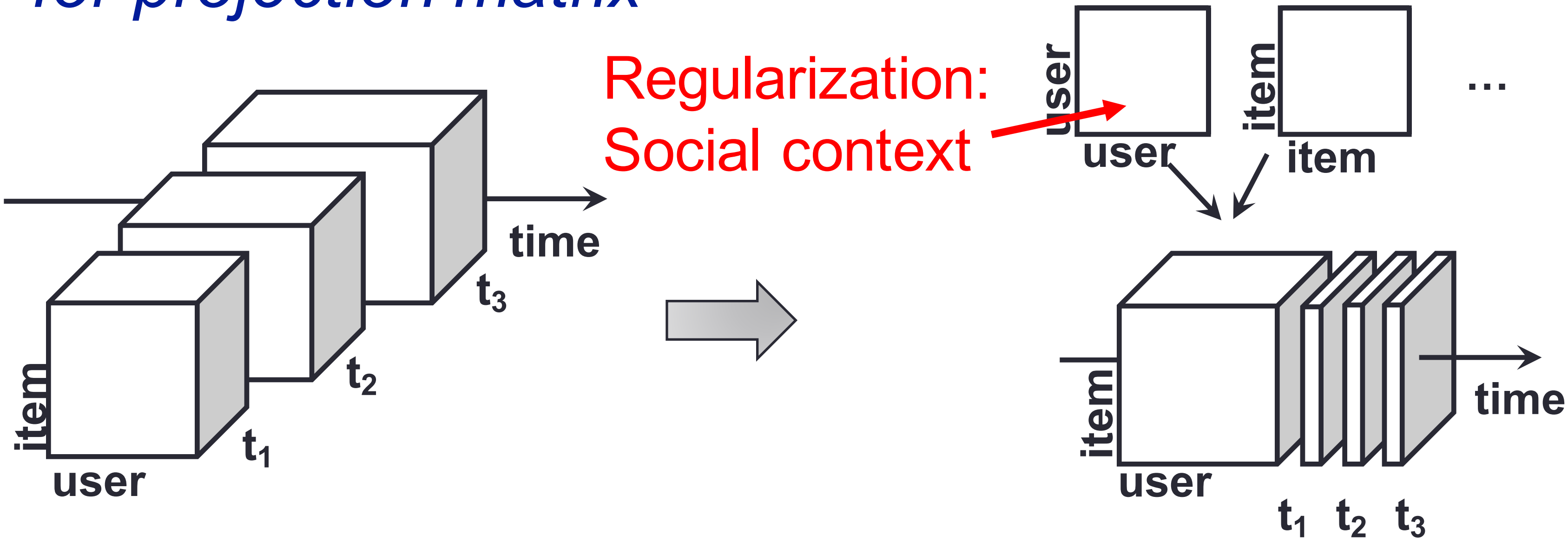
Modeling Spatiotemporal Contexts



Jiang et al. **Flexible Evolutionary Multi-faceted Analysis for Dynamic Behavioral Pattern Discovery.** *KDD*, 2014.

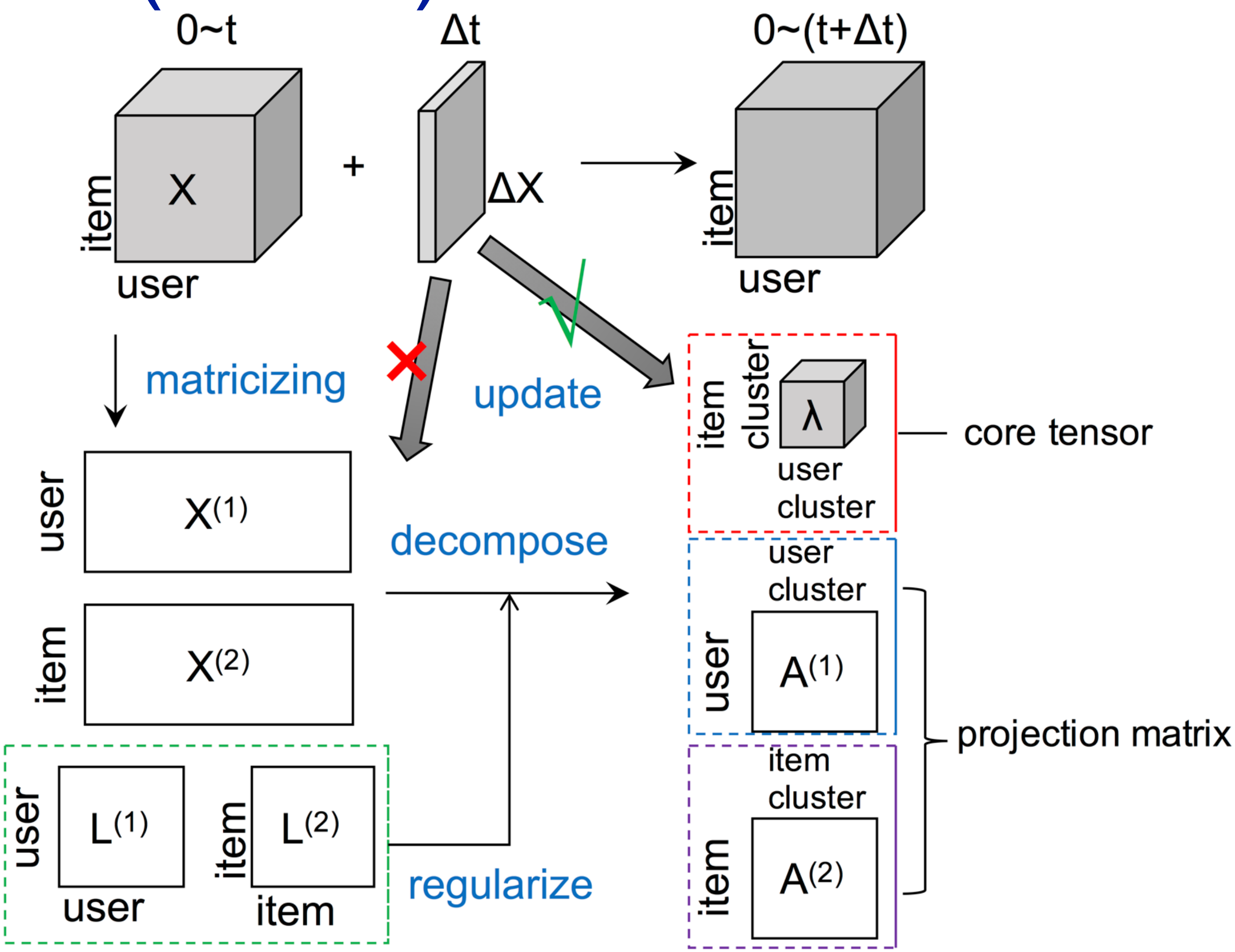
Challenges: Sparsity and Complexity

- Addressing sparsity: *Flexible regularization with auxiliary data*
- Addressing high complexity: *Incremental updates for projection matrix*



Jiang et al. **Flexible Evolutionary Multi-faceted Analysis for Dynamic Behavioral Pattern Discovery.** *KDD*, 2014.

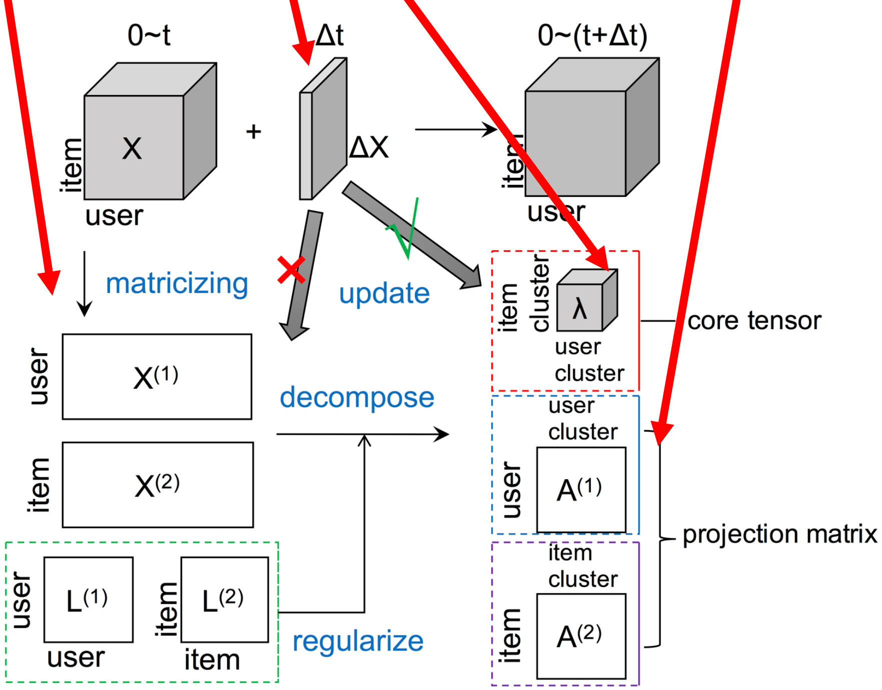
Flexible Evolutionary Multi-faceted Analysis (FEMA)



Jiang et al. **Flexible Evolutionary Multi-faceted Analysis for Dynamic Behavioral Pattern Discovery.** *KDD*, 2014.

Tensor Perturbation Theory

$$[(\mathbf{X}^{(\mathbf{m})} + \Delta\mathbf{X}^{(\mathbf{m})})(\mathbf{X}^{(\mathbf{m})} + \Delta\mathbf{X}^{(\mathbf{m})})^{\top} + \mu^{(m)}\mathbf{L}^{(\mathbf{m})}]$$
$$\cdot(\mathbf{a}_{\mathbf{i}}^{(\mathbf{m})} + \Delta\mathbf{a}_{\mathbf{i}}^{(\mathbf{m})}) = (\lambda_i^{(m)} + \Delta\lambda_i^{(m)})(\mathbf{a}_{\mathbf{i}}^{(\mathbf{m})} + \Delta\mathbf{a}_{\mathbf{i}}^{(\mathbf{m})})$$



FEMA Algorithm

Approximation

Require: $\mathcal{X}_t$, $\Delta\mathcal{X}_t$, $\mathbf{A}_t^{(m)}|_{m=1}^M$, $\lambda_t^{(m)}|_{m=1}^M$
  for $m = 1, \ldots, M$ **do**
    for $i = 1, \ldots, r^{(m)}$ **do**
      Compute $\Delta\lambda_{t,i}^{(m)}$ using

$$\boxed{\Delta\lambda_i^{(m)} = \mathbf{a}_i^{(m)\top}(\mathbf{X}^{(m)}\Delta\mathbf{X}^{(m)\top} + \Delta\mathbf{X}^{(m)}\mathbf{X}^{(m)\top})\mathbf{a}_i^{(m)}}$$

      and compute

$$\lambda_{t+1,i}^{(m)} = \lambda_{t,i}^{(m)} + \Delta\lambda_{t,i}^{(m)};$$

      Compute $\Delta\mathbf{a}_{t,i}^{(m)}$ using

$$\boxed{\Delta\mathbf{a}_i^{(m)} = \sum_{j\neq i}\frac{\mathbf{a}_j^{(m)\top}(\mathbf{X}^{(m)}\Delta\mathbf{X}^{(m)\top} + \Delta\mathbf{X}^{(m)}\mathbf{X}^{(m)\top})\mathbf{a}_i^{(m)}}{\lambda_i^{(m)} - \lambda_j^{(m)}}\mathbf{a}_j^{(m)}}$$

      and compute

$$\mathbf{a}_{t+1,i}^{(m)} = \mathbf{a}_{t,i}^{(m)} + \Delta\mathbf{a}_{t,i}^{(m)} \text{ and } \mathbf{A}_{t+1}^{(m)} = \{\mathbf{a}_{t+1,i}^{(m)}\};$$

    end for
  end for
  $\mathcal{Y}_{t+1} = (\mathcal{X}_t + \Delta\mathcal{X}_t)\prod_{m=1}^M \times_{(m)} \mathbf{A}_{t+1}^{(m)\mathbf{T}}$;
  return $\mathbf{A}_{t+1}^{(m)}|_{m=1}^M$, $\lambda_{t+1}^{(m)}|_{m=1}^M$, $\mathcal{Y}_{t+1}$

Bound Guarantee

core tensor

$$|\Delta\lambda_i^{(m)}| \leq 2(\lambda^{\max}_{\mathbf{X}^{(m)\top}\mathbf{X}^{(m)}})^{\frac{1}{2}}\|\Delta\mathbf{X}^{(m)}\|_2$$

$$|\Delta\mathbf{a}_i^{(m)}| \leq 2\|\Delta\mathbf{X}^{(m)}\|_2\sum_{j\neq i}\frac{(\lambda^{\max}_{\mathbf{X}^{(m)\top}\mathbf{X}^{(m)}})^{\frac{1}{2}}}{|\lambda_i^{(m)} - \lambda_j^{(m)}|}$$

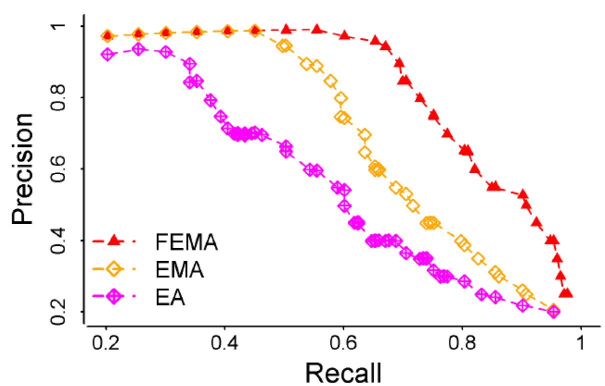
projection matrix

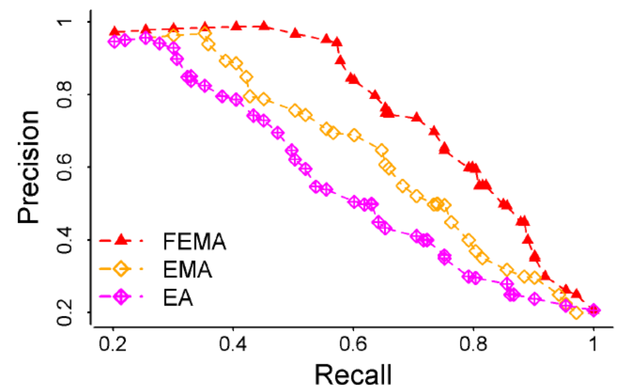
Jiang et al. **Flexible Evolutionary Multi-faceted Analysis for Dynamic Behavioral Pattern Discovery.** *KDD*, 2014.

Individual Behavior Prediction with FEMA

	Microsoft Academic Search		Tencent Weibo mentions “@”	
	MAE	RMSE	MAE	RMSE
FEMA	**0.735**	**0.944**	**0.894**	**1.312**
EMA	0.794	1.130	0.932	1.556
EA	0.979	1.364	1.120	1.873

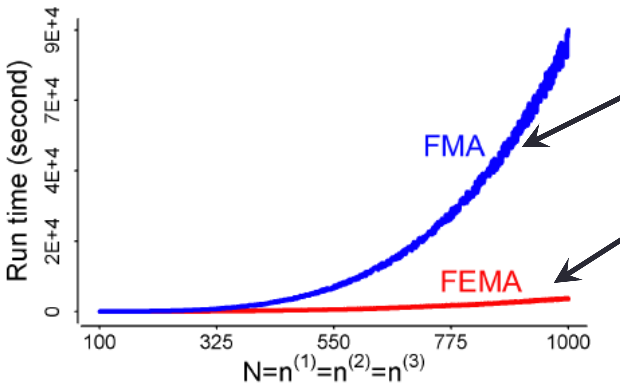
Precision vs Recall





Jiang et al. **Flexible Evolutionary Multi-faceted Analysis for Dynamic Behavioral Pattern Discovery.** *KDD*, 2014.

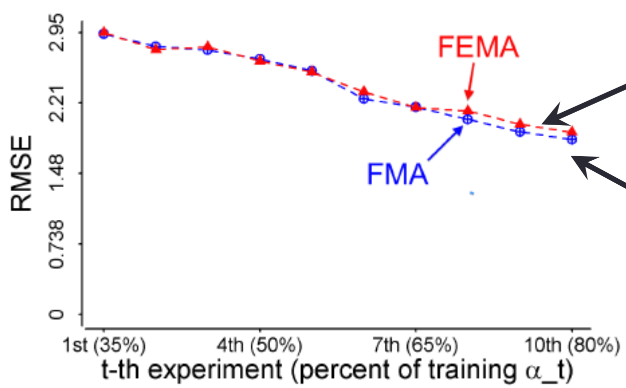
Individual Behavior Prediction with FEMA



Time vs Num. objects N

Re-decomposition:
Re-compute projection matrices

Evolutionary analysis:
Use ΔX to update λ and a



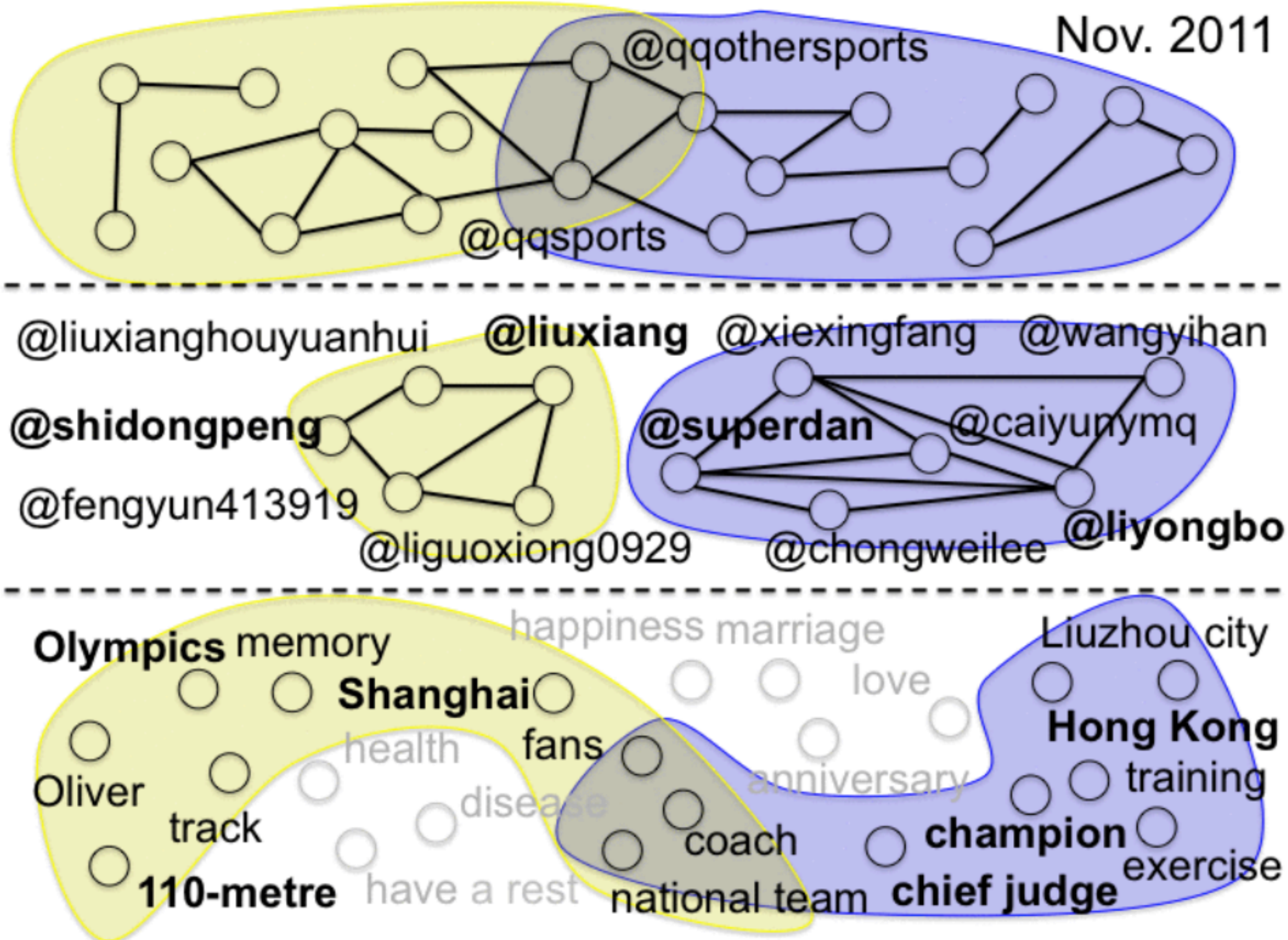
The loss is small.

Evolutionary analysis:
Use ΔX to update λ and a

Re-decomposition:
Re-compute projection matrices

Jiang et al. **Flexible Evolutionary Multi-faceted Analysis for Dynamic Behavioral Pattern Discovery.** *KDD*, 2014.

Behavioral Pattern: Fan@Idol#Word



Jiang et al. **Flexible Evolutionary Multi-faceted Analysis for Dynamic Behavioral Pattern Discovery.** *KDD*, 2014.

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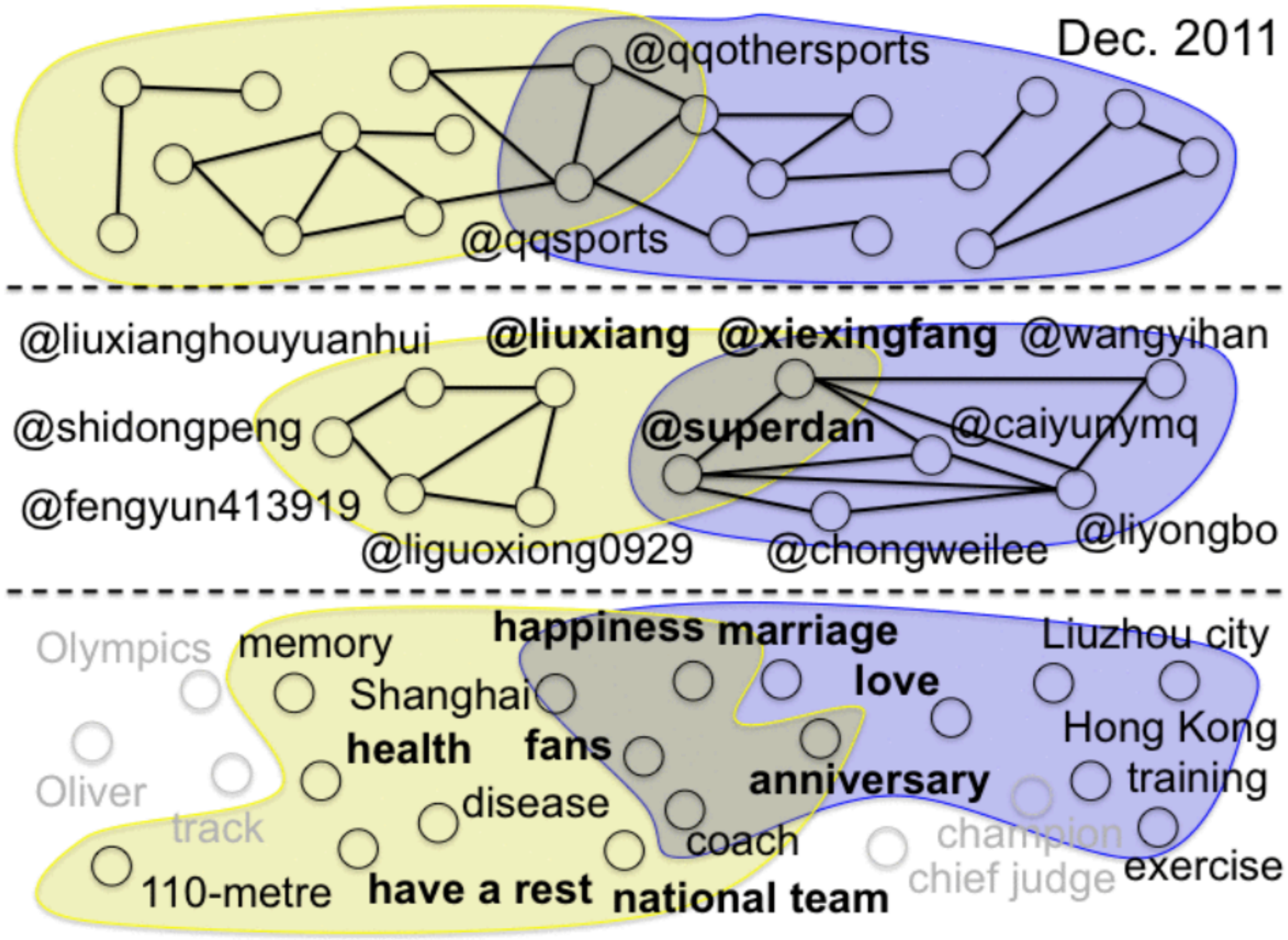


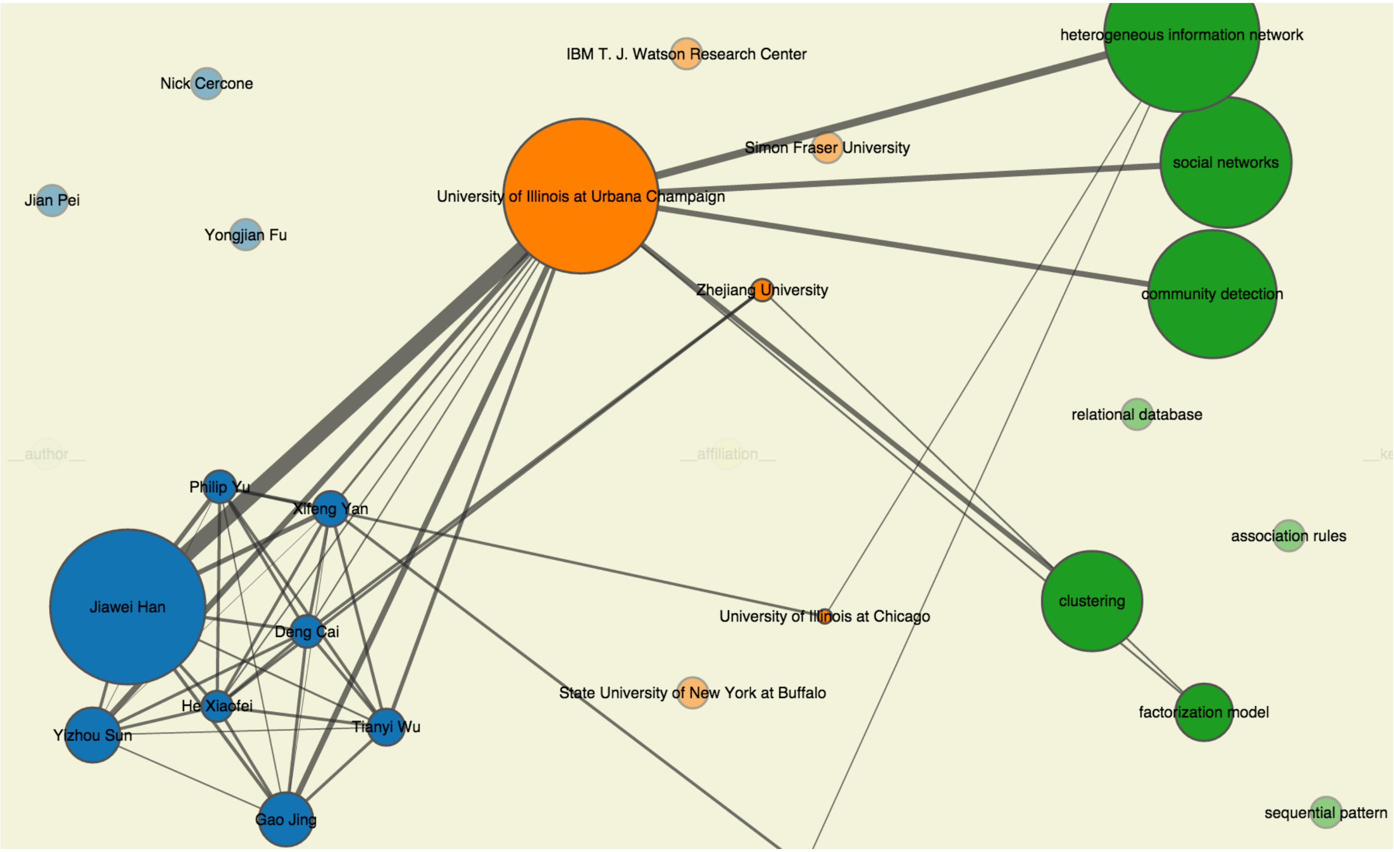
Jiang et al. **Flexible Evolutionary Multi-faceted Analysis for Dynamic Behavioral Pattern Discovery.** *KDD*, 2014.

Demo 1: Fan@Idol#Word

❖ http://www.meng-jiang.com/demos/fema/weibo/

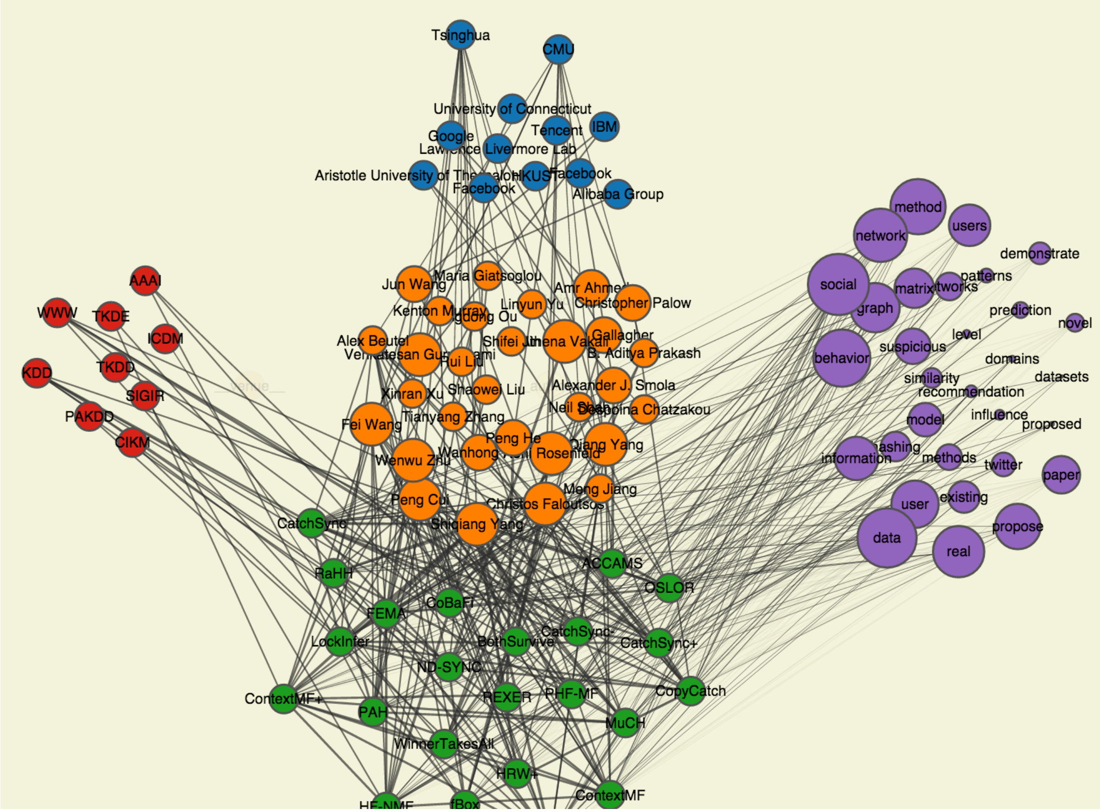
Demo 2: Author@Affiliation#Keyword

❖ http://www.meng-jiang.com/demos/fema/mas/



Demo 3: Author@Affiliation$Paper&Venue#Keyword

❖ http://www.meng-jiang.com/demos/hindblp/



Jiang et al. **Flexible Evolutionary Multi-faceted Analysis for Dynamic Behavioral Pattern Discovery.** *KDD*, 2014.

Modeling social contexts, spatio-temporal contexts: Amazing!

…however…

Modeling social contexts, spatio-temporal contexts: Amazing!

…however…

Sparsity

in one domain…

Besides Contexts: Multiple Domains

- Post

Jiang et al. **Social Recommendation across Multiple Relational Domains.** *CIKM*, 2012. **Social Recommendation with Cross-Domain Transferable Knowledge.** *TKDE*, 2015.

Besides Contexts: Multiple Domains

- Image

Jiang et al. **Social Recommendation across Multiple Relational Domains.** *CIKM*, 2012. **Social Recommendation with Cross-Domain Transferable Knowledge.** *TKDE*, 2015.

Besides Contexts: Multiple Domains

- Video

Jiang et al. **Social Recommendation across Multiple Relational Domains.** *CIKM*, 2012. **Social Recommendation with Cross-Domain Transferable Knowledge.** *TKDE*, 2015.

Besides Contexts: Multiple Domains

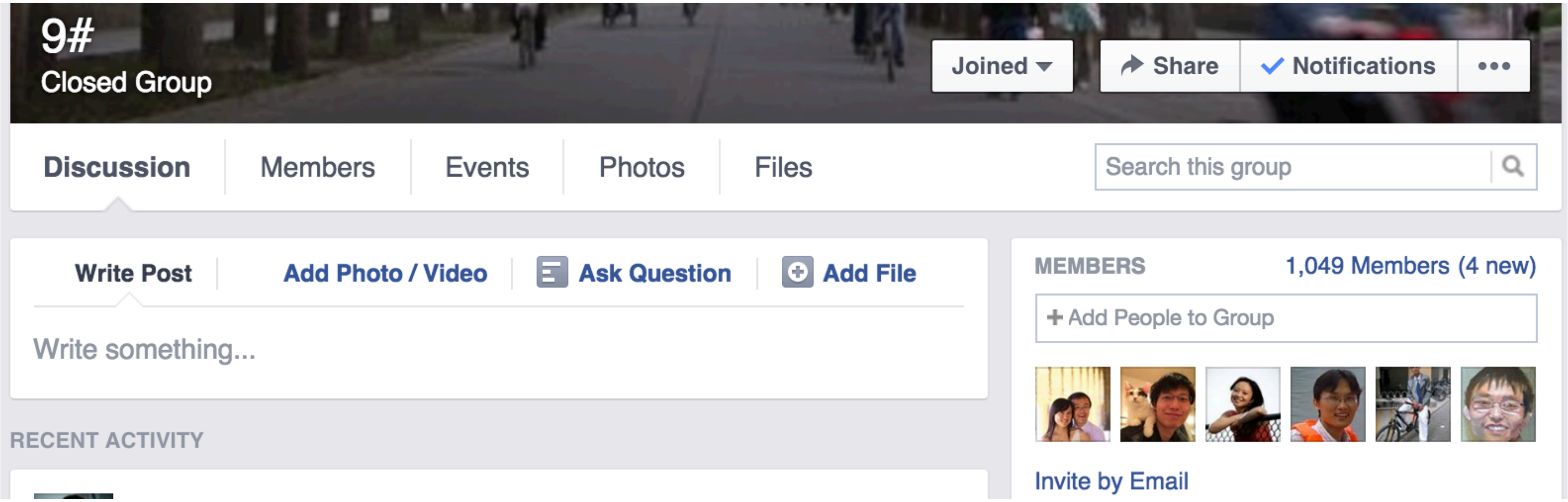
❖Social label

Religious Views	Christian
Interests	Basketball, writing, spending time w/ kids
Favorite Music	Miles Davis, John Coltrane, Bob Dylan, Stevie Wonder, Johann Sebastian Bach (cello suites), and The Fugees
Favorite Movies	Casablanca, Godfather I & II, Lawrence of Arabia and One Flew Over the Cuckoo's Nest
Favorite TV Shows	Sportscenter
Favorite Quotations	"The Arc of the moral universe is long, but it bends towards justice." (MLK)

Jiang et al. **Social Recommendation across Multiple Relational Domains.** *CIKM*, 2012. **Social Recommendation with Cross-Domain Transferable Knowledge.** *TKDE*, 2015.

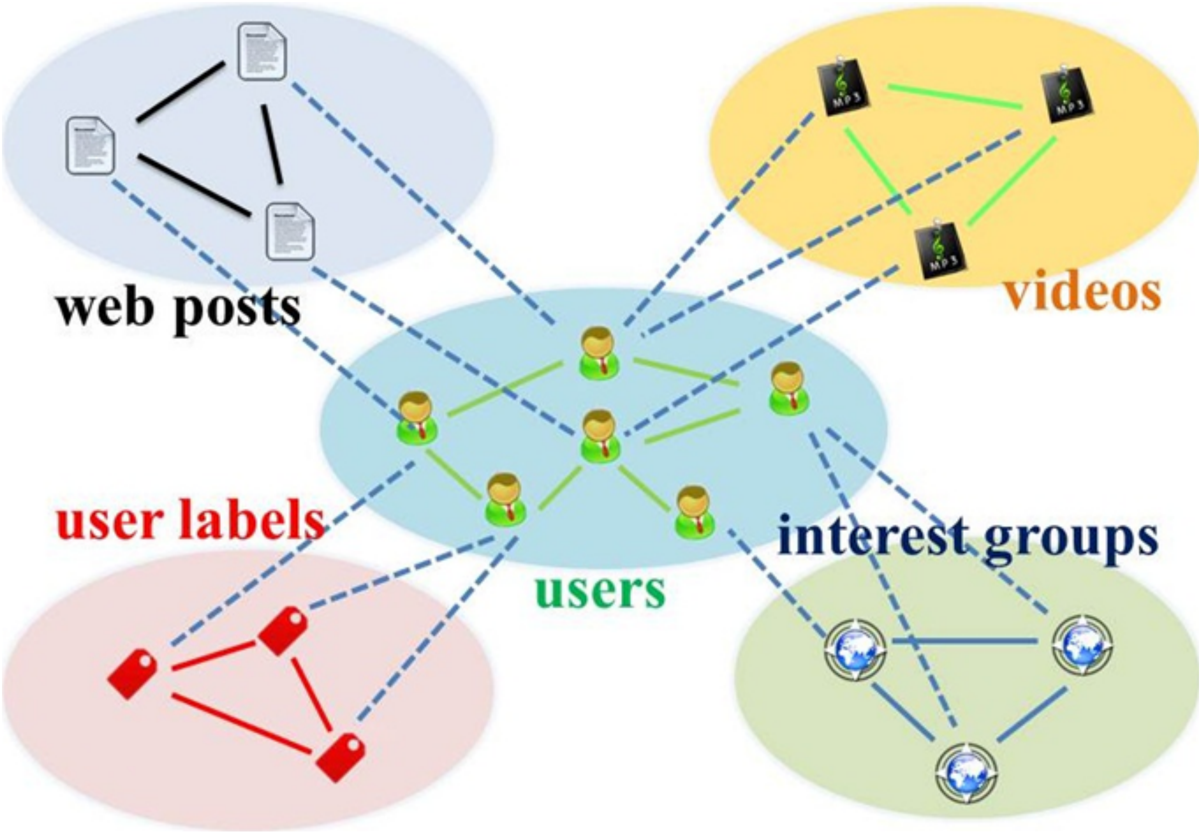
Besides Contexts: Multiple Domains

- Group



Jiang et al. **Social Recommendation across Multiple Relational Domains.** *CIKM*, 2012. **Social Recommendation with Cross-Domain Transferable Knowledge.** *TKDE*, 2015.

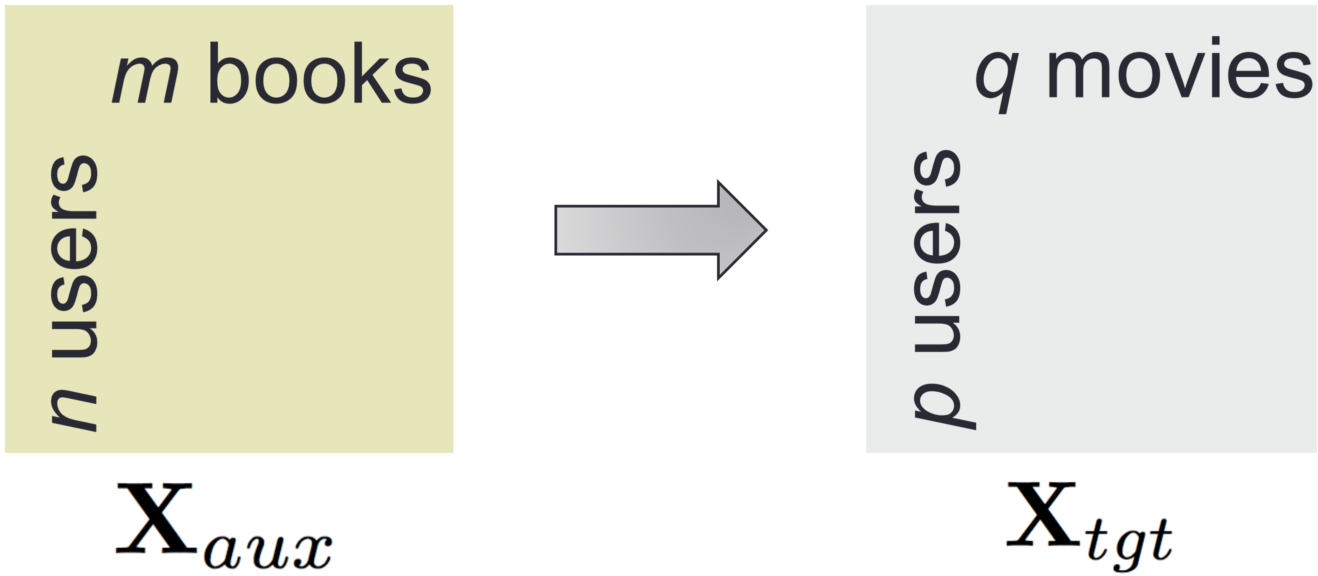
Besides Contexts: Multiple Domains



Jiang et al. **Social Recommendation across Multiple Relational Domains.** *CIKM*, 2012. **Social Recommendation with Cross-Domain Transferable Knowledge.** *TKDE*, 2015.

Traditional Cross-Domain CF

❖ Codebook Transfer (CBT)



Li et al. **Can Movies and Books Collaborate? Cross-Domain Collaborative Filtering for Sparsity Reduction.** *IJCAI*, 2009.

Traditional Cross-Domain CF

- Codebook Transfer (CBT) $n \times k$ $m \times l$

m books

n users

$\mathbf{X}_{aux}$

$$\min_{\mathbf{U}\geq 0, \mathbf{V}\geq 0, \mathbf{S}\geq 0} \left\|\mathbf{X}_{aux} - \mathbf{U}\mathbf{S}\mathbf{V}^\top\right\|_F^2$$

$$\text{s.t.} \quad \mathbf{U}^\top\mathbf{U} = \mathbf{I}, \mathbf{V}^\top\mathbf{V} = \mathbf{I},$$

Codebook = User Group × Item Group

$k \times l$

$$\mathbf{B} = [\mathbf{U}_{aux}^\top \mathbf{X}_{aux} \mathbf{V}_{aux}] \oslash [\mathbf{U}_{aux}^\top \mathbf{1}\mathbf{1}^\top \mathbf{V}_{aux}]$$

Li et al. **Can Movies and Books Collaborate? Cross-Domain Collaborative Filtering for Sparsity Reduction.** *IJCAI*, 2009.

Traditional Cross-Domain CF

- Codebook Transfer (CBT)

Codebook: $k \times l$

$q \times l$

$p \times k$

q movies

p users

$\mathbf{X}_{tgt}$

$$\min_{\substack{\mathbf{U}_{tgt}\in\{0,1\}^{p\times k}\\ \mathbf{V}_{tgt}\in\{0,1\}^{q\times l}}} \left\| [\mathbf{X}_{tgt} - \mathbf{U}_{tgt}\mathbf{B}\mathbf{V}_{tgt}^{\top}] \circ \mathbf{W} \right\|_F^2$$

$$\text{s.t.} \quad \mathbf{U}_{tgt}\mathbf{1} = \mathbf{1}, \mathbf{V}_{tgt}\mathbf{1} = \mathbf{1},$$

Traditional Cross-Domain CF

❖Codebook Transfer (CBT)

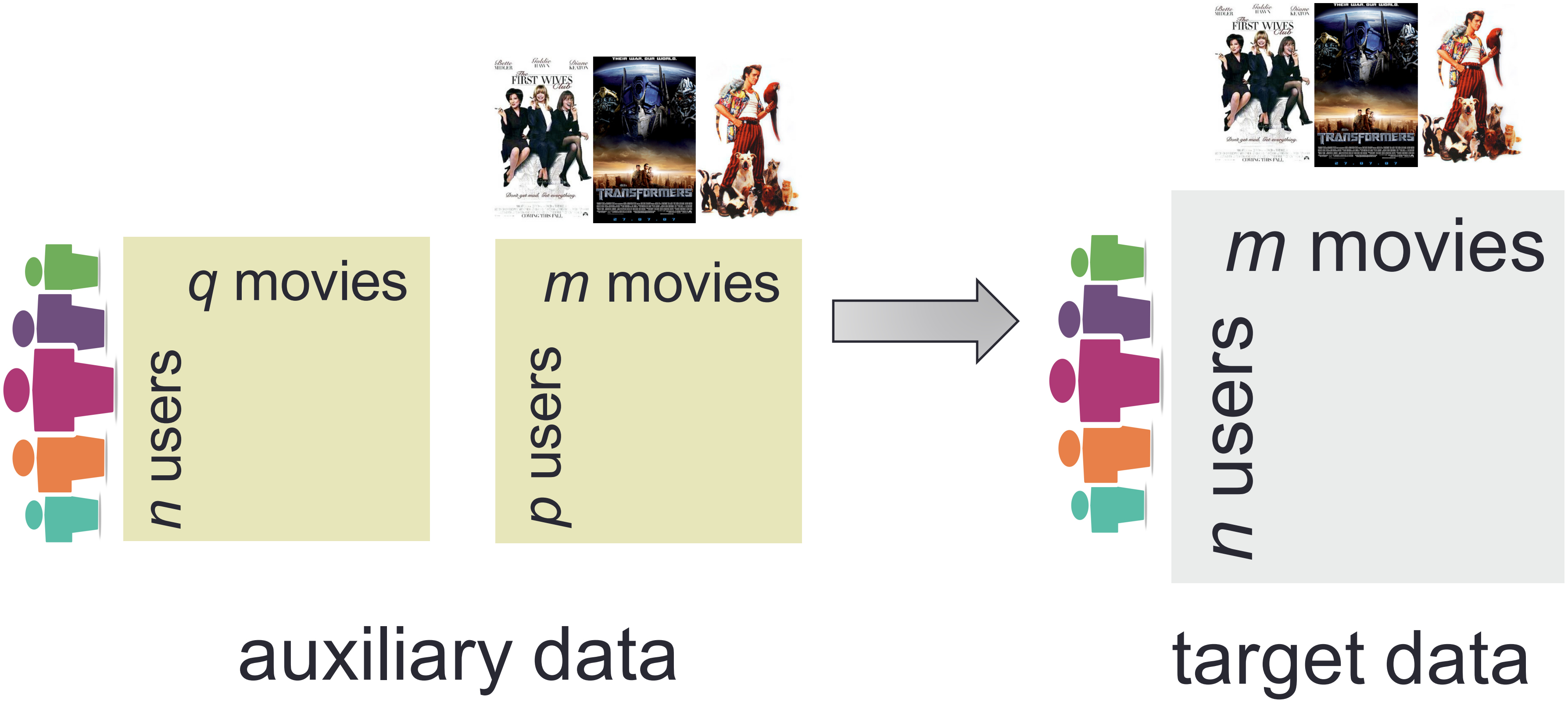
Table 1: MAE on MovieLens (average over 10 splits)

Training Set	Method	Given5	Given10	Given15
ML100	PCC	0.930	0.883	0.873
	CBS	0.874	0.845	0.839
	WLR	0.915	0.875	0.890
	CBT	**0.840**	**0.802**	**0.786**
ML200	PCC	0.905	0.878	0.878
	CBS	0.871	0.833	0.828
	WLR	0.941	0.903	0.883
	CBT	**0.839**	**0.800**	**0.784**
ML300	PCC	0.897	0.882	0.885
	CBS	0.870	0.834	0.819
	WLR	1.018	0.962	0.938
	CBT	**0.840**	**0.801**	**0.785**

Li et al. **Can Movies and Books Collaborate? Cross-Domain Collaborative Filtering for Sparsity Reduction.** *IJCAI*, 2009.

Traditional Cross-Domain CF

❖Coordinate System Transfer (CST)



Pan et al. **Transfer Learning in Collaborative Filtering for Sparsity Reduction.** *AAAI*, 2010.

Traditional Cross-Domain CF

❖Coordinate System Transfer (CST)

Auxiliary data:

$$\min_{\mathbf{U}^{(i)},\mathbf{V}^{(i)},\mathbf{B}^{(i)}} ||\mathbf{Y}^{(i)} \odot (\mathbf{R}^{(i)} - \boxed{\mathbf{U}^{(i)}}\mathbf{B}^{(i)}\boxed{\mathbf{V}^{(i)T}})||_F^2$$

Target data:

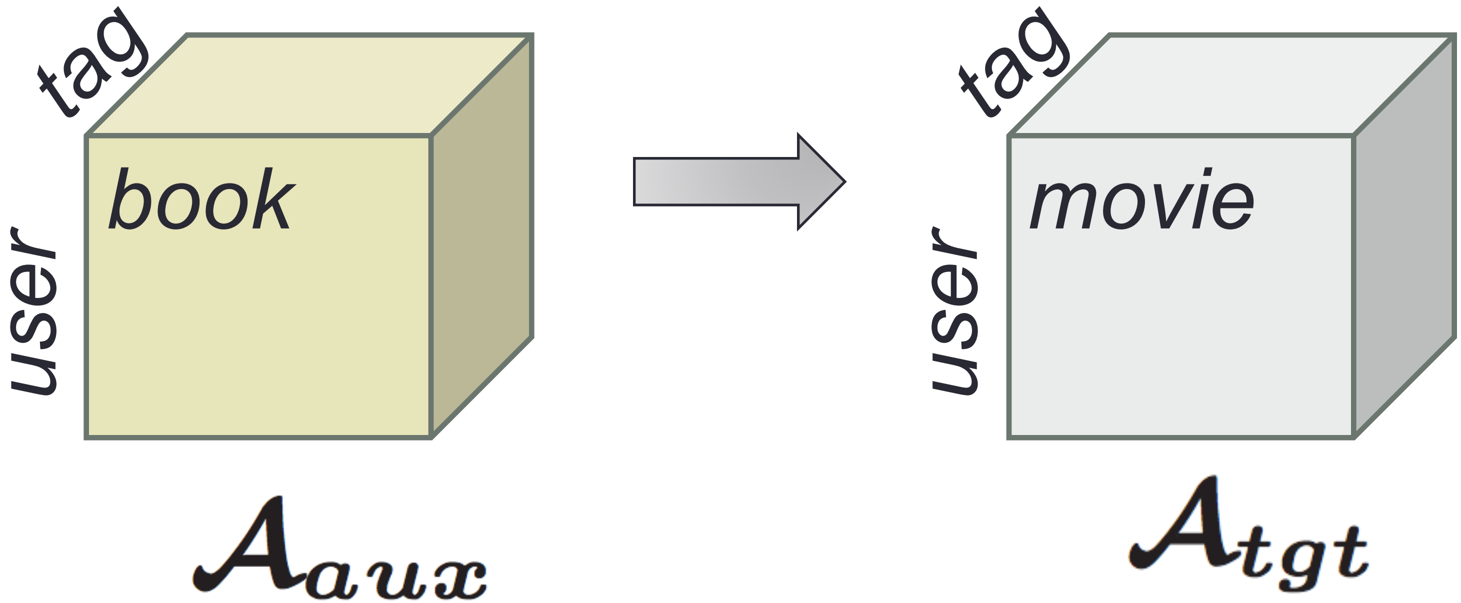
$$\min_{\mathbf{U},\mathbf{V},\mathbf{B}} ||\mathbf{Y} \odot (\mathbf{R} - \mathbf{U}\mathbf{B}\mathbf{V}^T)|| + \boxed{\frac{\rho_u}{2}||\mathbf{U} - \mathbf{U}_0||_F^2} + \boxed{\frac{\rho_v}{2}||\mathbf{V} - \mathbf{V}_0||_F^2}$$

$$\text{s.t.} \quad \mathbf{U}^T\mathbf{U} = \mathbf{I}, \mathbf{V}^T\mathbf{V} = \mathbf{I}$$

Pan et al. **Transfer Learning in Collaborative Filtering for Sparsity Reduction.** *AAAI*, 2010.

Traditional Cross-Domain CF

❖FUSE



Chen et al. **Making Recommendation from Multiple Domains.** *KDD*, 2013.

Traditional Cross-Domain CF

- FUSE

$$\mathcal{A}^{*}_{tgt} = \mathcal{A}^{cluster}_{aux} \times_1 \hat{U}^{(1)}_{tgt} \times_2 \hat{U}^{(2)}_{tgt} \times_3 \hat{U}^{(3)}_{tgt}$$

$$\boldsymbol{f} = \min_{\hat{U}^{(1)}_{tgt} \cdots \hat{U}^{(3)}_{tgt}} \boxed{||\mathcal{A} - \mathcal{A}^{*}_{tgt}||^2_F}$$
$$+\lambda \cdot \sum_{r=1}^{R} tr([\hat{U}^{(1)}_{tgt}]^T (\boldsymbol{D}^{(r)} - \boldsymbol{F}^{(r)}) \hat{U}^{(1)}_{tgt})$$

Traditional Cross-Domain CF

- FUSE

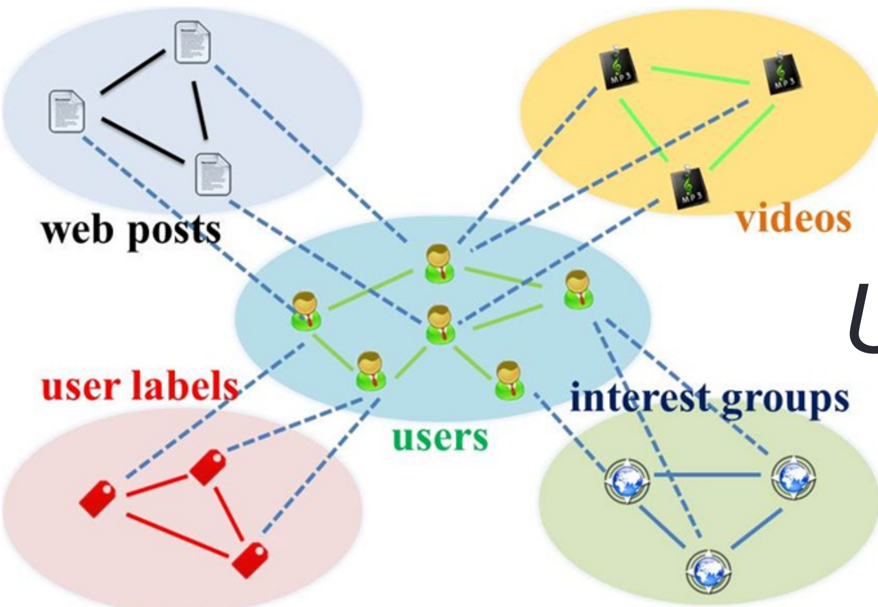
$$[\hat{\boldsymbol{U}}^{(1)}_{\boldsymbol{tgt}}]_{*r} \leftarrow [\hat{\boldsymbol{U}}^{(1)}_{\boldsymbol{tgt}}]_{*r} \circledast \frac{[\boldsymbol{A}_{(1)}\boldsymbol{S}^T_{(1)}]_{*r} + \lambda \boldsymbol{F}^{(r)}[\hat{\boldsymbol{U}}^{(1)}_{\boldsymbol{tgt}}]_{*r}}{[\hat{\boldsymbol{U}}^{(1)}_{\boldsymbol{tgt}}\boldsymbol{S}_{(1)}\boldsymbol{S}^T_{(1)}]_{*r} + \lambda \boldsymbol{D}^{(r)}[\hat{\boldsymbol{U}}^{(1)}_{\boldsymbol{tgt}}]_{*r}}$$

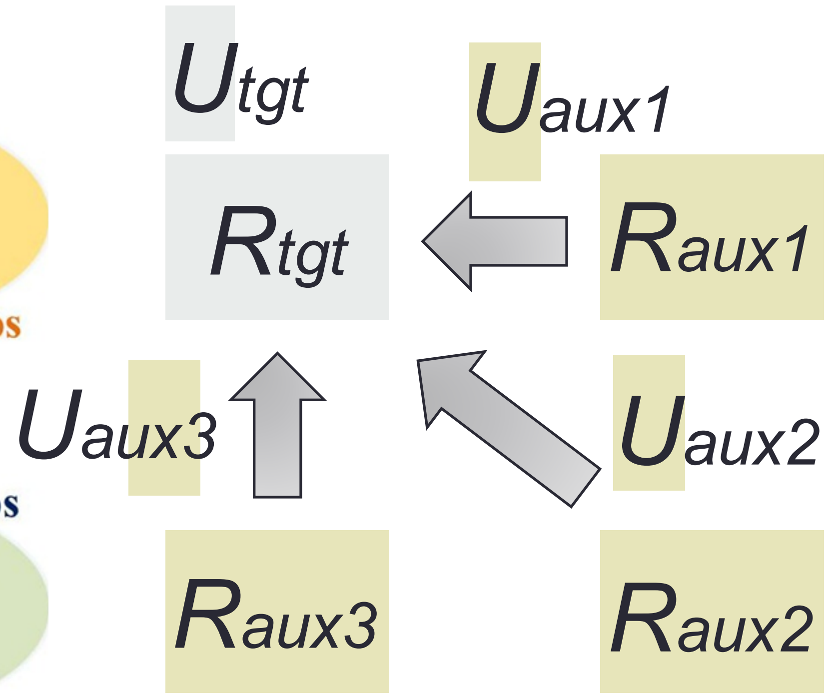
Gradient Descent Methods

$$\hat{\boldsymbol{U}}^{(2)}_{\boldsymbol{tgt}} \leftarrow \hat{\boldsymbol{U}}^{(2)}_{\boldsymbol{tgt}} \circledast \frac{\boldsymbol{A}_{(2)}\boldsymbol{S}^T_{(2)}}{\hat{\boldsymbol{U}}^{(2)}_{\boldsymbol{tgt}}\boldsymbol{S}_{(2)}\boldsymbol{S}^T_{(2)}}$$

$$\hat{\boldsymbol{U}}^{(3)}_{\boldsymbol{tgt}} \leftarrow \hat{\boldsymbol{U}}^{(3)}_{\boldsymbol{tgt}} \circledast \frac{\boldsymbol{A}_{(3)}\boldsymbol{S}^T_{(3)}}{\hat{\boldsymbol{U}}^{(3)}_{\boldsymbol{tgt}}\boldsymbol{S}_{(3)}\boldsymbol{S}^T_{(3)}}$$

When Social Recommendation Meets Multiple Domains

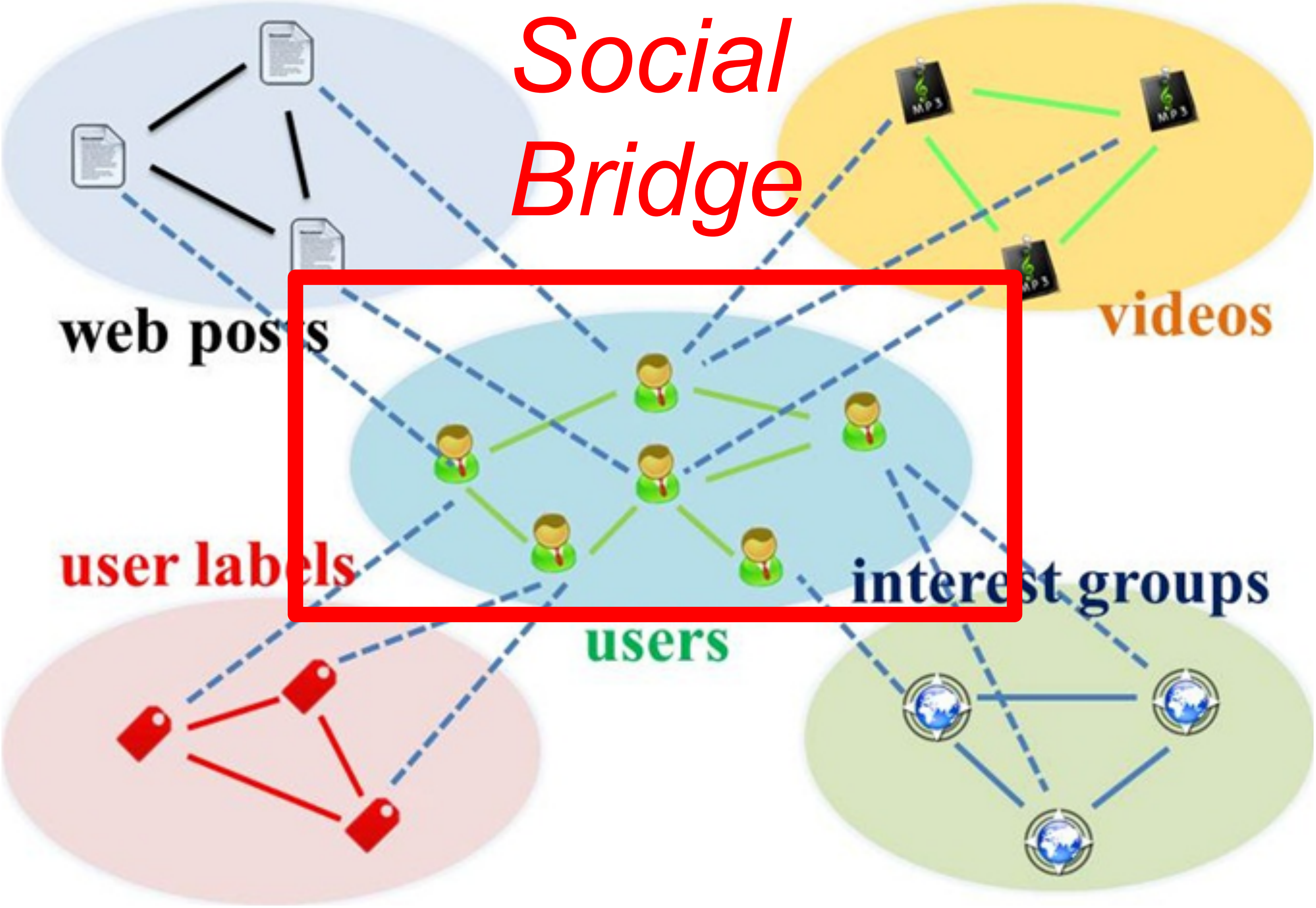




Bridge: User × Cluster

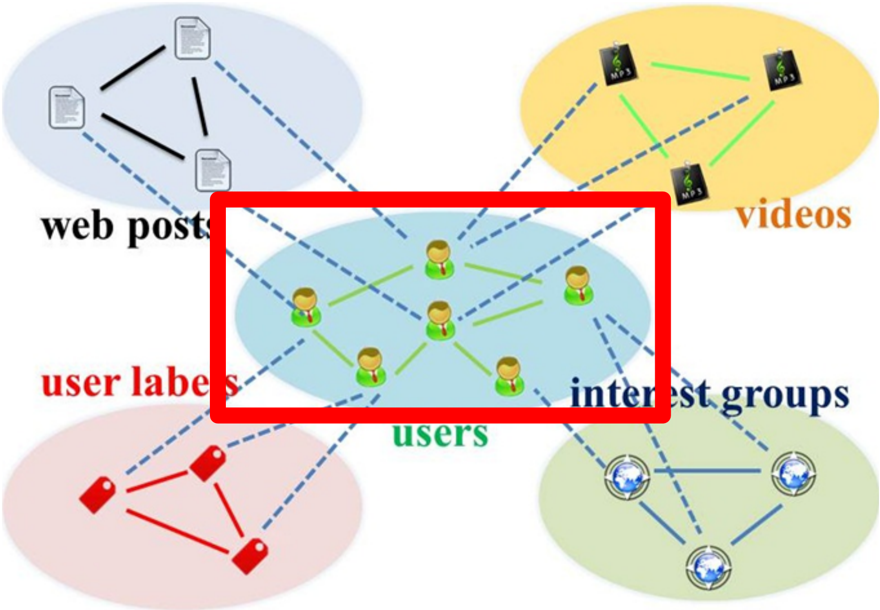
Jiang et al. **Social Recommendation across Multiple Relational Domains.** *CIKM*, 2012. **Social Recommendation with Cross-Domain Transferable Knowledge.** *TKDE*, 2015.

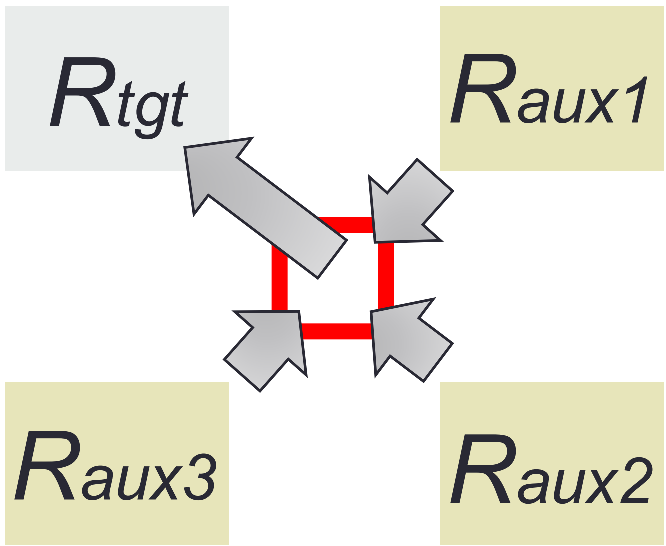
When Social Recommendation Meets Multiple Domains



Jiang et al. **Social Recommendation across Multiple Relational Domains.** *CIKM*, 2012. **Social Recommendation with Cross-Domain Transferable Knowledge.** *TKDE*, 2015.

When Social Recommendation Meets Multiple Domains



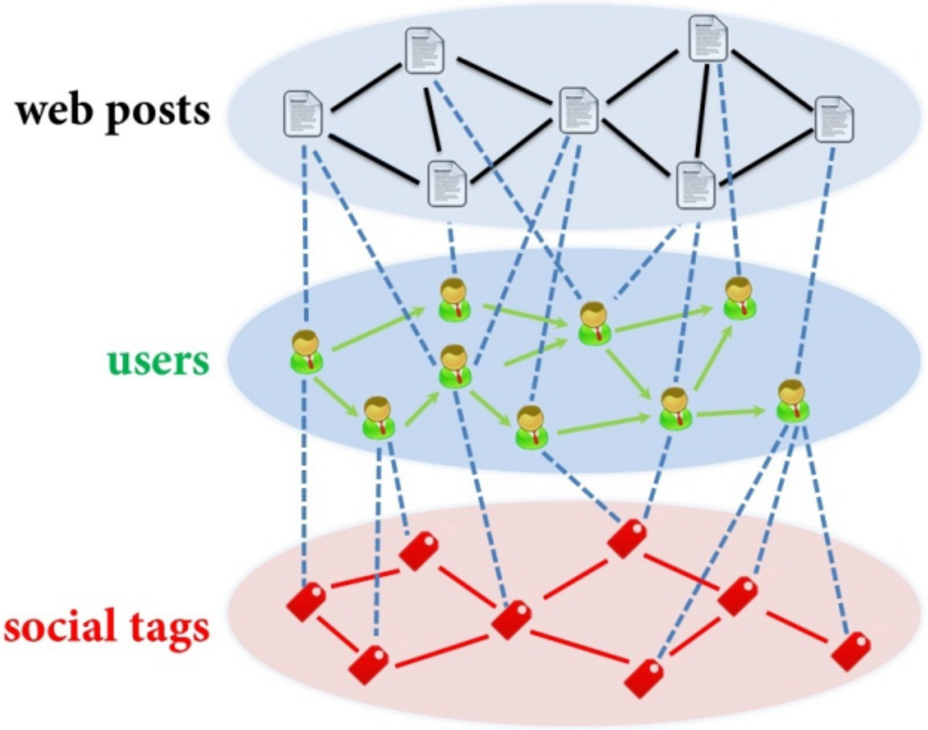


Bridge: User × User

Jiang et al. **Social Recommendation across Multiple Relational Domains.** *CIKM*, 2012. **Social Recommendation with Cross-Domain Transferable Knowledge.** *TKDE*, 2015.

Hybrid Random Walk

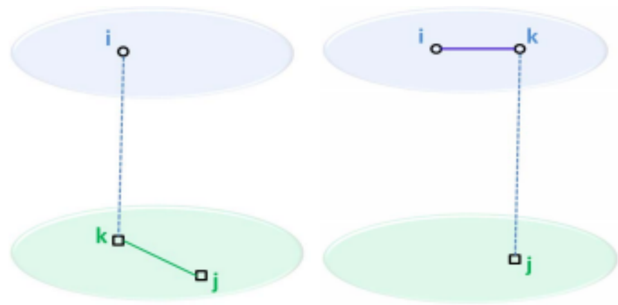
- Starting with a Second-Order Start-Structured Graph



Jiang et al. **Social Recommendation across Multiple Relational Domains.** *CIKM*, 2012. **Social Recommendation with Cross-Domain Transferable Knowledge.** *TKDE*, 2015.

Hybrid Random Walk

❖Updating cross-domain links



(a) Route 1 (b) Route 2

$$p_{ij}^{(\mathcal{UP})^+} = \delta \sum_{u_k \in \mathcal{U}} r_{ik}^{(\mathcal{U})} p_{kj}^{(\mathcal{UP})^+} + (1-\delta) \sum_{p_k \in \mathcal{P}} p_{ik}^{(\mathcal{UP})^+} r_{kj}^{(\mathcal{P})}$$

$$p_{ij}^{(\mathcal{UP})^-} = \delta \sum_{u_k \in \mathcal{U}} r_{ik}^{(\mathcal{U})} p_{kj}^{(\mathcal{UP})^-} + (1-\delta) \sum_{p_k \in \mathcal{P}} p_{ik}^{(\mathcal{UP})^-} r_{kj}^{(\mathcal{P})}$$

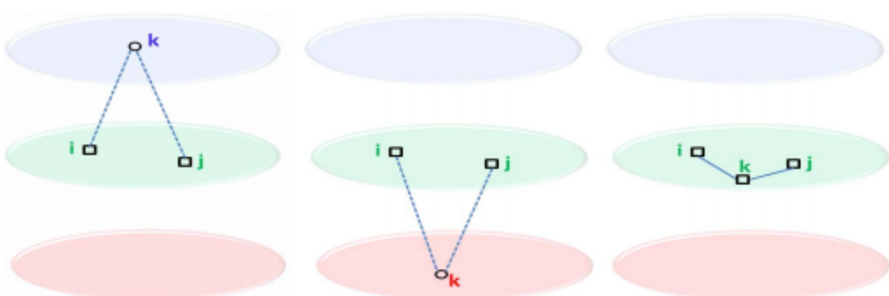
$$p_{ij}^{(\mathcal{UT})^+} = \eta \sum_{u_k \in \mathcal{U}} r_{ik}^{(\mathcal{U})} p_{kj}^{(\mathcal{UT})^+} + (1-\eta) \sum_{t_k \in \mathcal{T}} p_{ik}^{(\mathcal{UT})^+} r_{kj}^{(\mathcal{T})}$$

$$\mathbf{P}^{(\mathcal{UP})^+}(t+1) = \delta \mathbf{R}^{(\mathcal{U})}(t)\mathbf{P}^{(\mathcal{UP})^+}(t) + (1-\delta)\mathbf{P}^{(\mathcal{UP})^+}(t)\mathbf{R}^{(\mathcal{P})}$$

$$\mathbf{P}^{(\mathcal{UP})^-}(t+1) = \delta \mathbf{R}^{(\mathcal{U})}(t)\mathbf{P}^{(\mathcal{UP})^-}(t) + (1-\delta)\mathbf{P}^{(\mathcal{UP})^-}(t)\mathbf{R}^{(\mathcal{P})}$$

$$\mathbf{P}^{(\mathcal{UT})^+}(t+1) = \eta \mathbf{R}^{(\mathcal{U})}(t)\mathbf{P}^{(\mathcal{UT})^+}(t) + (1-\eta)\mathbf{P}^{(\mathcal{UT})^+}(t)\mathbf{R}^{(\mathcal{T})}$$

❖Updating within-domain links



(a) Route 1 (b) Route 2 (c) Route 3

$$r_{ij}^{(\mathcal{U})} = \tau^{(\mathcal{P})}\Big(\mu \sum_{p_k \in \mathcal{P}} p_{ik}^{(\mathcal{UP})^+} p_{jk}^{(\mathcal{UP})^+} + (1-\mu) \sum_{p_k \in \mathcal{P}} p_{ik}^{(\mathcal{UP})^-} p_{jk}^{(\mathcal{UP})^-}\Big)$$
$$+\tau^{(\mathcal{T})} \sum_{t_k \in \mathcal{T}} p_{ik}^{(\mathcal{UT})^+} p_{jk}^{(\mathcal{UT})^+} + \tau^{(\mathcal{U})} \sum_{u_k \in \mathcal{U}} r_{ik}^{(\mathcal{U})} r_{kj}^{(\mathcal{U})} \qquad (12)$$

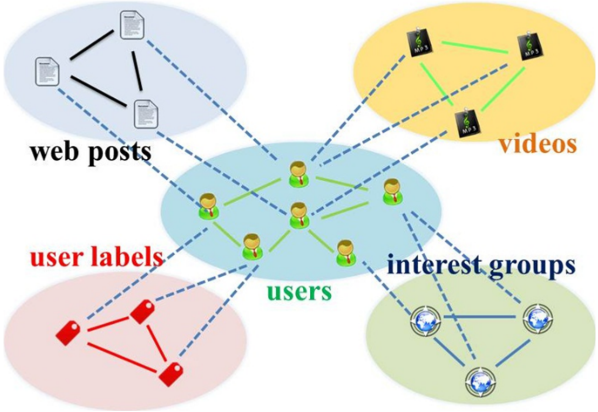
$$\mathbf{R}^{(\mathcal{U})}(t+1) =$$
$$\tau^{(\mathcal{P})}\Big(\mu \mathbf{P}^{(\mathcal{UP})^+}(t)\mathbf{P}^{(\mathcal{UP})^+}(t)^T + (1-\mu)\mathbf{P}^{(\mathcal{UP})^-}(t)\mathbf{P}^{(\mathcal{UP})^-}(t)^T\Big)$$
$$+\tau^{(\mathcal{T})}\mathbf{P}^{(\mathcal{UT})^+}(t)\mathbf{P}^{(\mathcal{UT})^+}(t)^T + \tau^{(\mathcal{U})}\mathbf{R}^{(\mathcal{U})}(t)\mathbf{R}^{(\mathcal{U})}(t)^T \qquad (13)$$

Jiang et al. **Social Recommendation across Multiple Relational Domains.** *CIKM*, 2012. **Social Recommendation with Cross-Domain Transferable Knowledge.** *TKDE*, 2015.

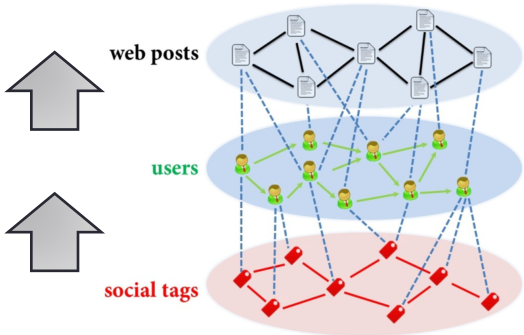
Hybrid Random Walk

❖High-Order Star-Structured Graph

$$
\begin{aligned}
\mathbf{P}^{(\mathcal{U}\mathcal{D}_i)^+}(t+1) &= \delta_i \mathbf{R}^{(\mathcal{U})}(t)\mathbf{P}^{(\mathcal{U}\mathcal{D}_i)^+}(t) + (1-\delta_i)\mathbf{P}^{(\mathcal{U}\mathcal{D}_i)^+}(t)\mathbf{R}^{(\mathcal{D}_i)} \\
\mathbf{P}^{(\mathcal{U}\mathcal{D}_i)^-}(t+1) &= \delta_i \mathbf{R}^{(\mathcal{U})}(t)\mathbf{P}^{(\mathcal{U}\mathcal{D}_i)^-}(t) + (1-\delta_i)\mathbf{P}^{(\mathcal{U}\mathcal{D}_i)^-}(t)\mathbf{R}^{(\mathcal{D}_i)} \\
\mathbf{R}^{(\mathcal{U})}(t+1) &= \sum_{\mathcal{D}_i \in \mathcal{D}} \tau_i \mu_i \mathbf{P}^{(\mathcal{U}\mathcal{D}_i)^+}(t)\mathbf{P}^{(\mathcal{U}\mathcal{D}_i)^+}(t)^T \\
&+ \sum_{\mathcal{D}_i \in \mathcal{D}} \tau_i (1-\mu_i)\mathbf{P}^{(\mathcal{U}\mathcal{D}_i)^-}(t)\mathbf{P}^{(\mathcal{U}\mathcal{D}_i)^-}(t)^T \\
&+ \tau^{(\mathcal{U})}\mathbf{R}^{(\mathcal{U})}(t)\mathbf{R}^{(\mathcal{U})}(t)^T \qquad (20)
\end{aligned}
$$



Hybrid Random Walk



Comparing with Random Walk with Restarts Models

Algorithm	MAE	Precision	Recall	F1	Kendall's $\hat{\tau}$
HRW	**0.227±1.5e-3**	**0.711±1.3e-3**	0.921±1.4e-3	**0.802±1.1e-3**	**0.792±2.5e-3**
BRW-R_U-P (TrustWalker)	0.276±1.1e-3	0.657±7.6e-4	**0.935±9.8e-4**	0.772±7.6e-4	0.774±1.6e-3
BRW-R_U	0.282±5.3e-3	0.655±4.0e-3	0.921±1.2e-2	0.765±7.7e-3	0.725±2.8e-3
BRW-W_U-P	0.292±1.1e-3	0.666±7.0e-4	0.900±5.2e-4	0.765±6.6e-4	0.725±8.5e-4
BRW-W_U (ItemRank)	0.318±1.4e-3	0.671±1.5e-3	0.713±2.4e-3	0.691±1.2e-3	0.661±2.2e-3
BRW-P	0.438±2.6e-4	0.571±3.4e-4	0.499±4.2e-4	0.532±3.2e-4	0.606±2.3e-4

Comparing with Social Recommendation Baselines

Algorithm	MAE	Precision	Recall	F1	Kendall's $\hat{\tau}$
HRW	**0.227±1.5e-3**	**0.711±1.3e-3**	0.921±1.4e-3	**0.802±1.1e-3**	**0.792±2.5e-3**
BRW-R_U-P (TrustWalker) [10]	0.276±1.1e-3	0.657±7.6e-4	0.935±9.8e-4	0.772±7.6e-4	0.774±1.6e-3
BRW-W_U (ItemRank) [8]	0.318±1.4e-3	0.671±1.5e-3	0.713±2.4e-3	0.691±1.2e-3	0.661±2.2e-3
MCF [5]	0.352±2.3e-4	0.592±1.8e-3	**0.951±6.0e-4**	0.730±1.3e-3	0.582±4.3e-4
CF [22]	0.506±3.4e-4	0.552±1.5e-3	0.589±7.2e-4	0.570±1.0e-3	0.540±5.2e-4

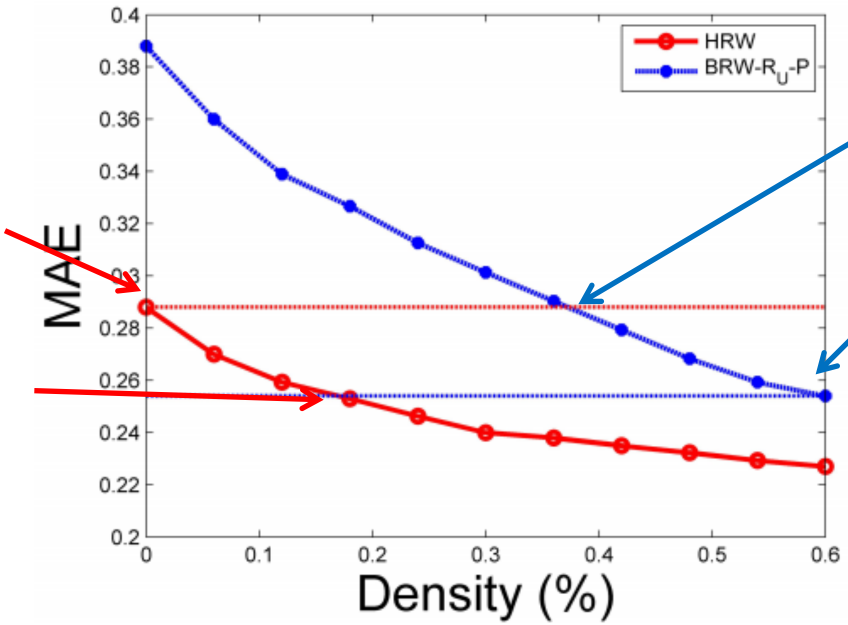
Jiang et al. **Social Recommendation across Multiple Relational Domains.** *CIKM*, 2012. **Social Recommendation with Cross-Domain Transferable Knowledge.** *TKDE*, 2015.

Hybrid Random Walk

- Knowledge transfer from auxiliary domains improves cold-start users' behavior prediction
  - Using aux. (label) data, saving ***60-70%*** tgt. (post) data

0 user-post
100% user-label

18% user-post
100% user-label



35% user-post
0 user-label

60% user-post
0 user-label

Jiang et al. **Social Recommendation across Multiple Relational Domains.** *CIKM*, 2012. **Social Recommendation with Cross-Domain Transferable Knowledge.** *TKDE*, 2015.

Besides Cross-Domain…

- How about Cross-Platform?
- Partially aligned/overlapped users!

Little is Much: Bridging Cross-Platform Behaviors through Overlapped Crowds
by M. Jiang, P. Cui, N. J. Yuan, X. Xie, S. Yang. AAAI Conference on Artificial Intelligence (AAAI) , 2016.

Questions for Modeling Individual Behavior

- What is individual behavior in social networks?
- Why should we study individual behavior?
- What are the state-of-the-art models?
  - Modeling behaviors and social relations
  - Modeling social contexts
  - Modeling spatiotemporal contexts
  - Modeling multiple domains in social networks

Summary for Modeling Individual Behavior

- Like, Reply, Share, Retweet, Favorite, Comment …
- Pattern discovery, prediction and social recommendation
- Memory based social recommenders
  - TidalTrust, MoleTrust, TrustWalker
- Model based social recommenders
  - SoRec, “Social Trust” Ensemble, SoReg
- ContextMF: Social contexts (preference & influence)
- FEMA: Spatiotemporal contexts (multi-faceted & dynamic)
- Traditional cross-domain CF
  - CBT, CST, FUSE
- Hybrid Random Walk: Social bridging multiple domains