Data-Driven Behavioral Analytics:
Observations, Representations and Models

Meng Jiang (UIUC)
Peng Cui (Tsinghua)
Jiawei Han (UIUC)

http://www.meng-jiang.com/tutorial-cikm16.html

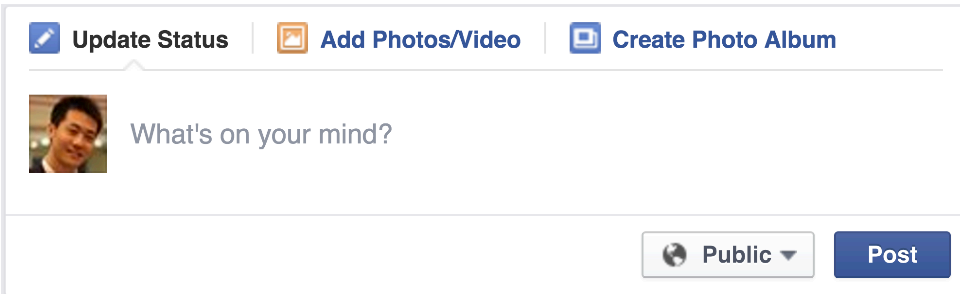
Tutorial in CIKM 2016, October 24, Indianapolis, IN

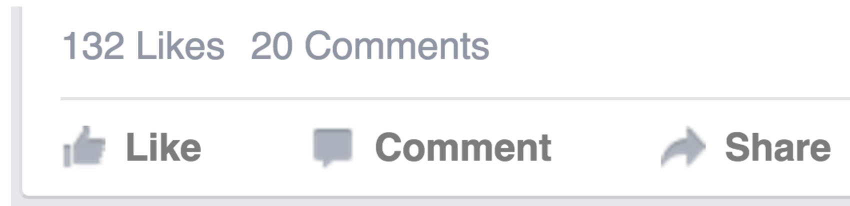
I. Mining behavior networks with social and spatiotemporal contexts

I.1. Behavior prediction and recommendation

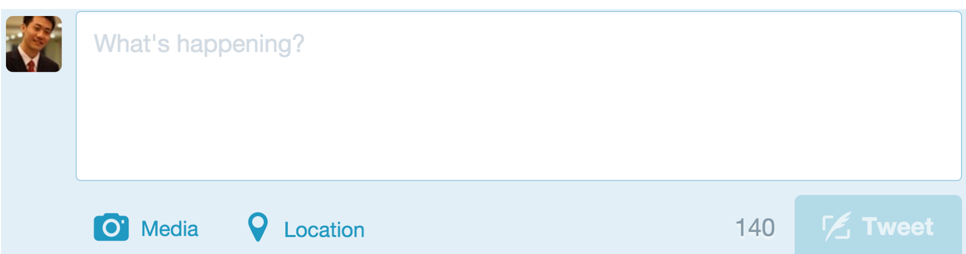
Behavior in Social Networks

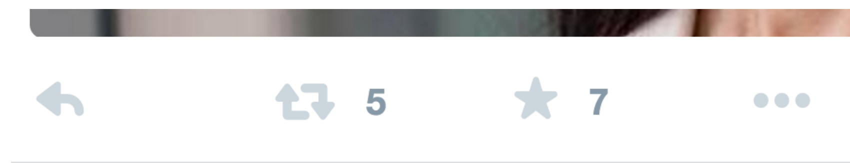
- **Facebook:** Post, Like, Comment, Share



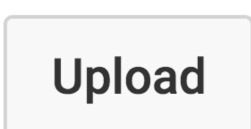


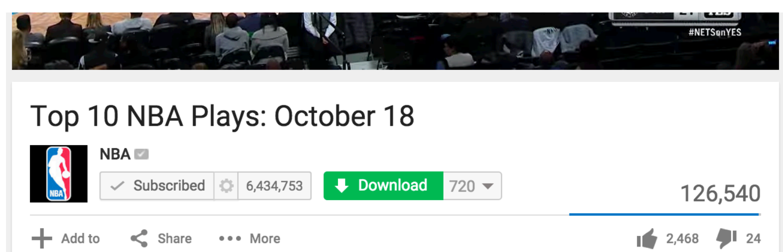
- **Twitter:** Post, Reply, Retweet, Favorite





- **YouTube:** Upload, Subscribe, Download, Share, Comment

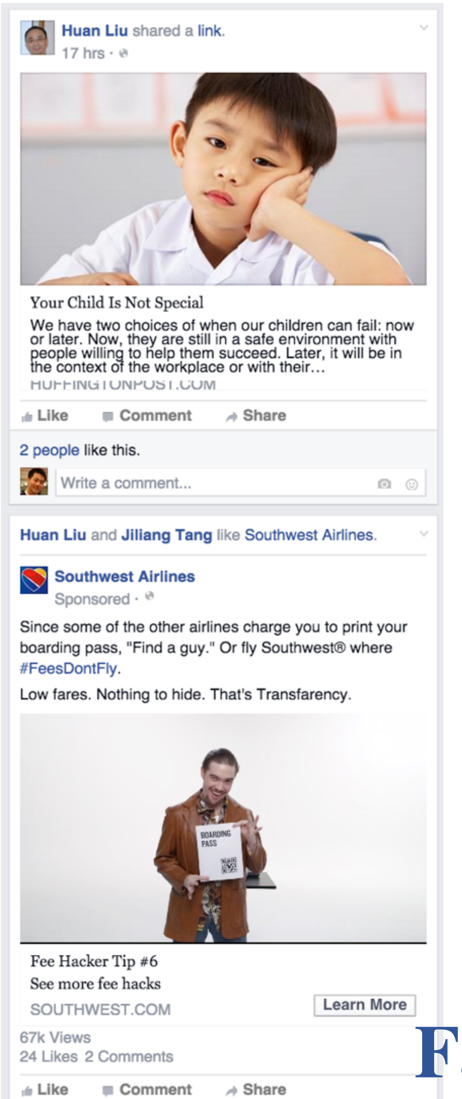


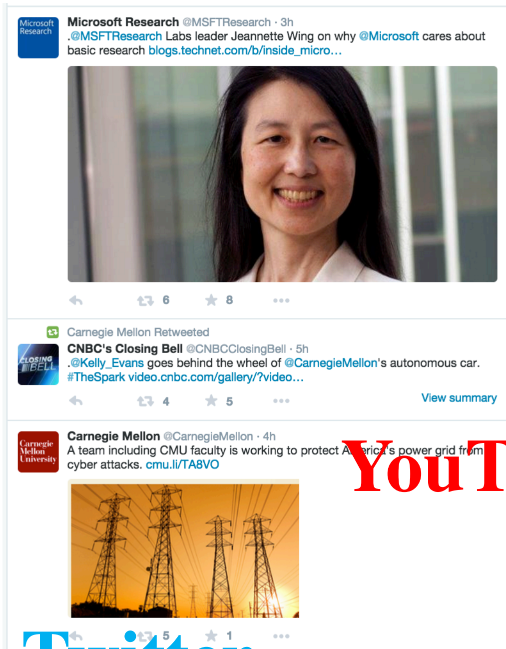


Behavior in Social Networks

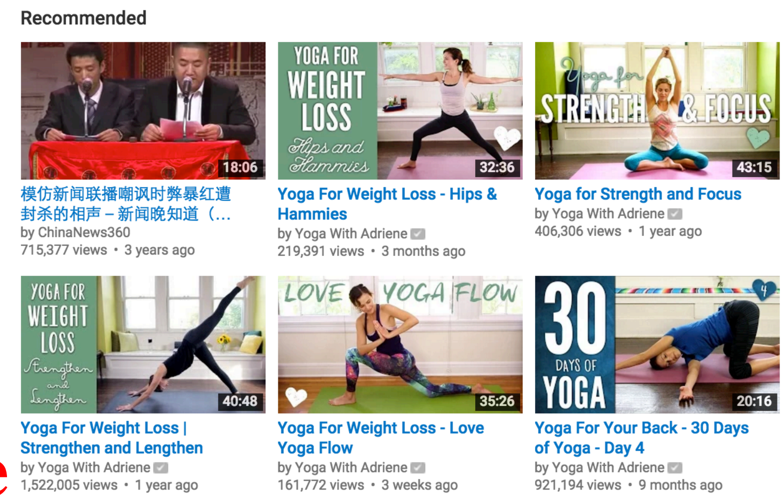
Like
Reply
Share
Favorite
Retweet
Comment
Subscribe
Download
Add to
Send
Pin it
Visit
……

Social Recommender Systems

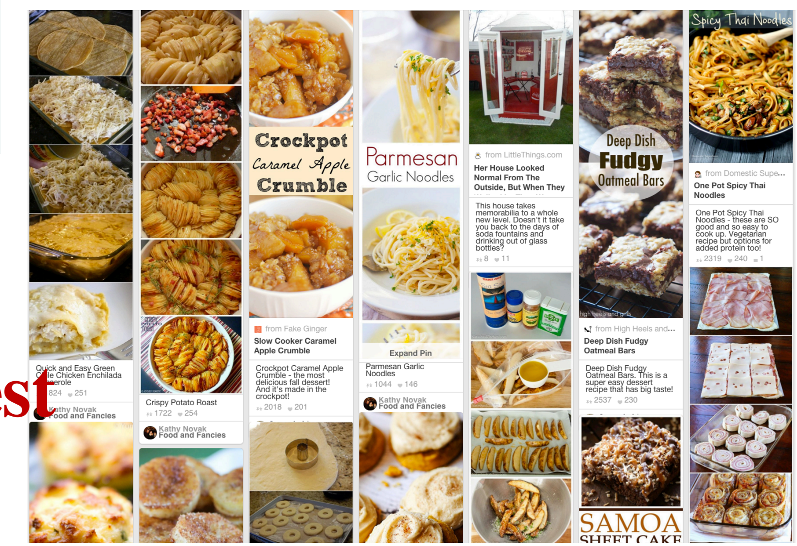




Twitter



YouTube



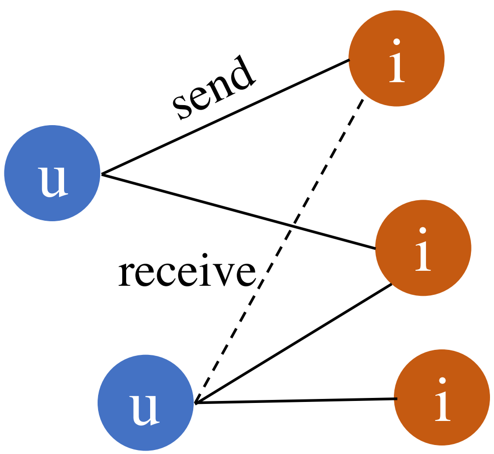
Pinterest

Facebook

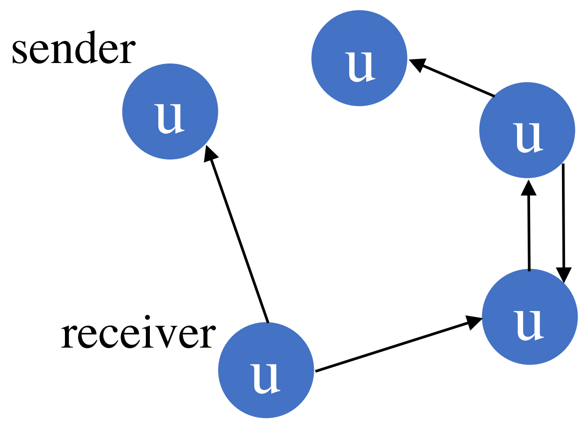
Social Recommender Systems

- April 20, 2011: **Tencent Weibo** visited Tsinghua University
  - Low *conversion rate* (< 6%): #retweets per feed request
  - Can we build a ***social recommender system***?
  - **Given**

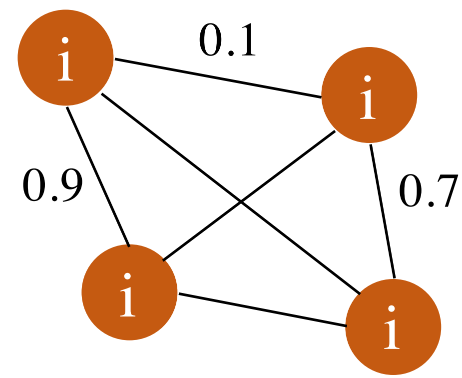
User-item behavior network



User-user social network



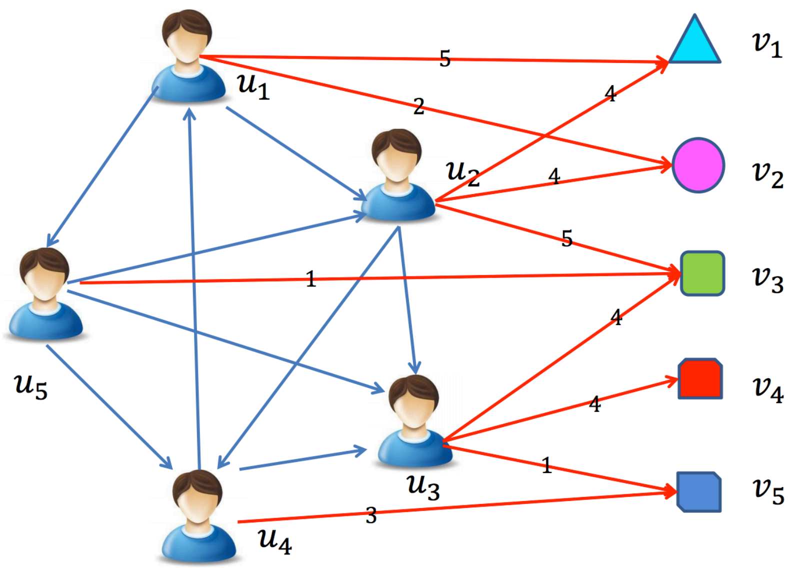
Content similarity (topic level) [Blei *et al.*]



  - **Predict** which tweet/item a user will retweet.

Traditional Recommender Systems

- Assumed that users are independent and identically distributed (user-movie, user-book, *etc*.)



	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., TF-IDF)
  - 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

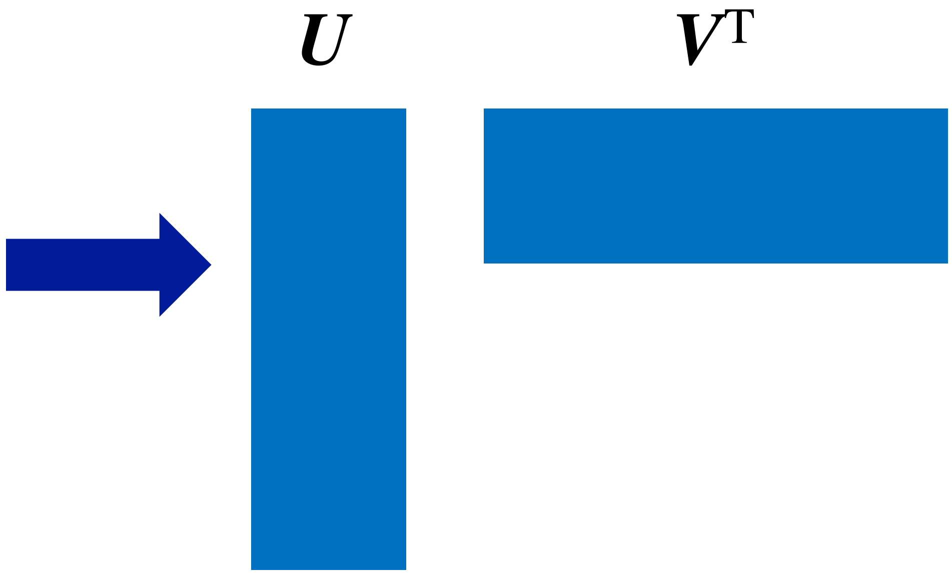
Tang et al. **Social Recommendation: A Review.** *Social Network Analysis and Mining*, 2013. Springer.

Matrix Factorization (MF) based CF

- 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 (MF) based CF

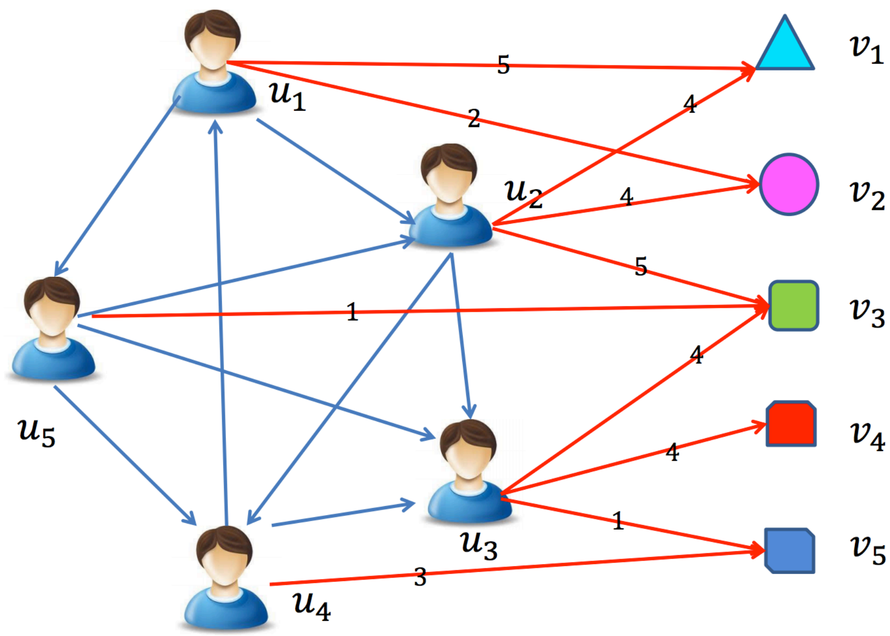
- Low-rank MF on the user-item rating matrix ***R***
- User preference vector ***U***
- Item characteristic vector ***V***
- Observed weight matrix ***W***

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

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	?	?

Memory based Social Recommender

- **TidalTrust**

rating

(user i, item m)

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

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

average rating (user a)

rating (user u, item i)

average rating (user u)

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

predicted rating (user a, item i)

trust from social relation (user a, user u)

Massa et al. **Trust-aware recommender systems.** *RecSys*, 2007.

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)

Jamali et al. **TrustWalker: A Random Walk Model for Combining Trust-based and Item-based Recommendation.** *KDD*, 2009.

Model based Social Recommender

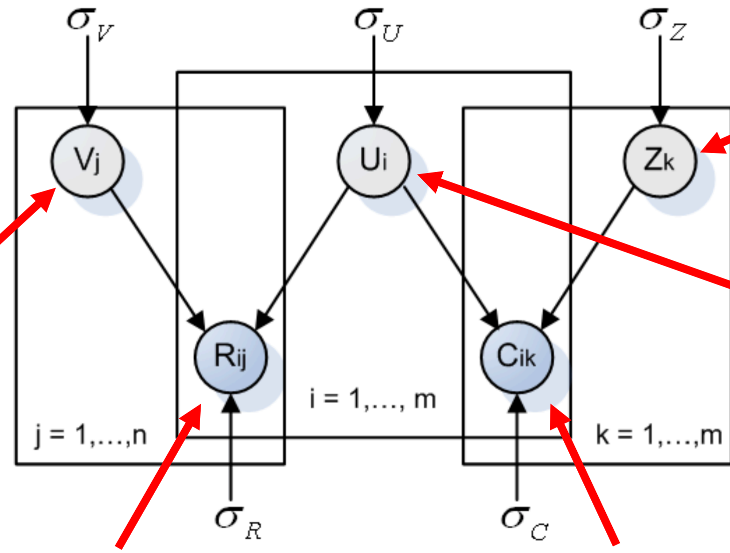
- Optimization methods such as gradient based methods can be applied to find a well-worked optimal solution.
- MF has a nice probabilistic interpretation with Gaussian noise.
- MF is very flexible and allows us to include prior knowledge.

$$
\begin{aligned}
& \textit{Social Recommendation CF} \\
= \; & \textit{Basic CF} + \textit{Social Information Model}
\end{aligned}
$$

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

Model based Social Recommender

- **SoRec**



factor vector

item vector

user vector

***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

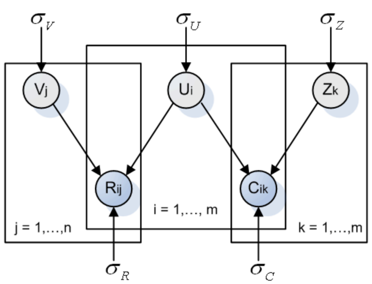
Ma et al. **Social Recommendation Using Probabilistic Matrix Factorization.** *CIKM*, 2008.
Improving Recommender Systems by Incorporating Social Contextual Information. *TIS*, 2011.

Model based Social Recommender

- SoRec

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

R



Gaussian distribution

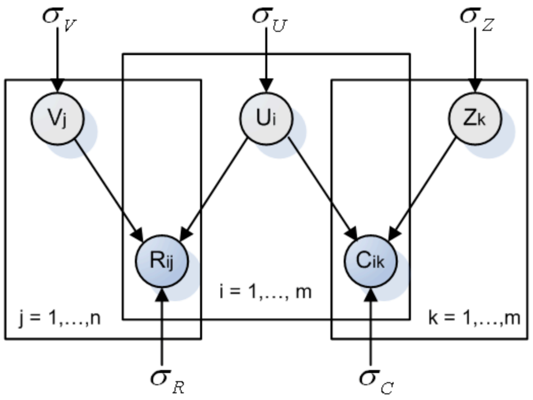
Logistic function

Observed

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

Model based Social Recommender

- **SoRec**



behavioral term

social term

$$\mathcal{L}(R,C,U,V,Z) =$$

$$\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}^{R}\underline{(r_{ij} - g(U_i^T V_j))^2} + \frac{\lambda_C}{2}\sum_{i=1}^{m}\sum_{k=1}^{m} I_{ik}^{C}\underline{(c_{ik}^{*} - g(U_i^T Z_k))^2}$$

$$\underline{+\frac{\lambda_U}{2}\|U\|_F^2 + \frac{\lambda_V}{2}\|V\|_F^2 + \frac{\lambda_Z}{2}\|Z\|_F^2}, \qquad (9)$$

regularization terms

Model based Social Recommender

- **SoRec**

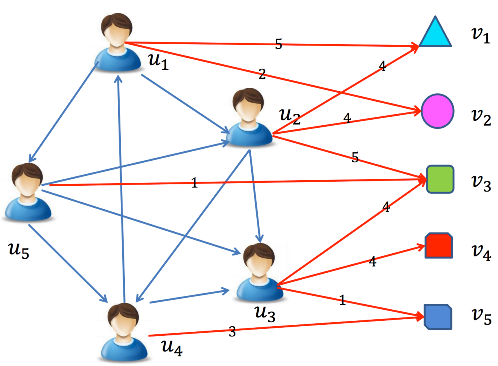
Gradient Descent Methods

deviate of Logistic function

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

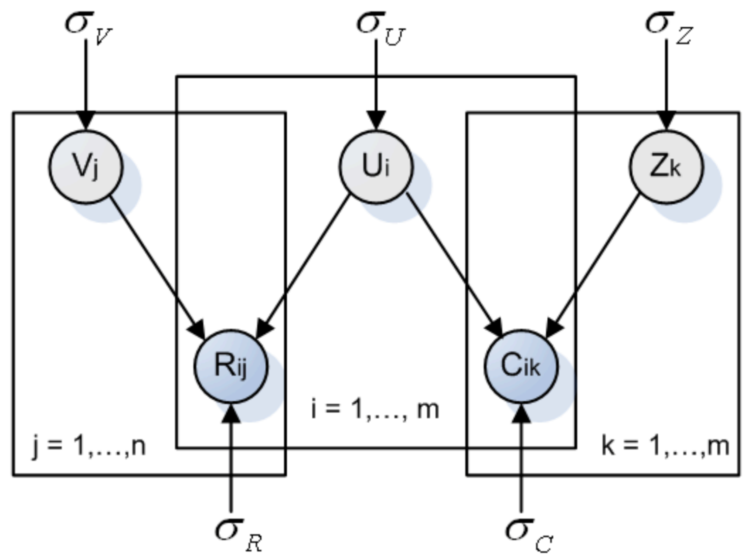
Model based Social Recommender

- SoRec



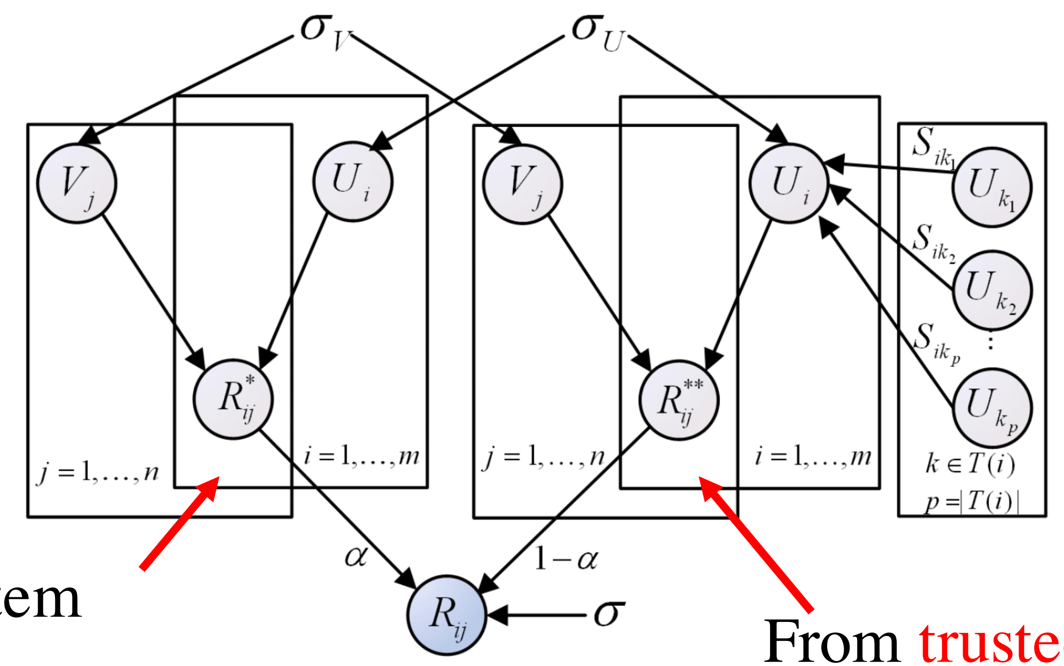
	u_1	u_2	u_3	u_4	u_5
u_1	0	1	0	0	1
u_2	0	0	1	1	0
u_3	0	0	0	0	0
u_4	1	0	1	0	0
u_5	0	1	1	1	0

	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	?	?



Model based Social Recommender

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



From user-item matrix

Operation "plus"

From trusted friends

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

- "Social Trust" Ensemble

From user-item matrix

From trusted friends

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

Model based Social Recommender

- "Social Trust" Ensemble

Gradient Descent Methods

$$
\begin{aligned}
\frac{\partial \mathcal{L}}{\partial U_i} = & \alpha \sum_{j=1}^{n} I_{ij}^{R} g'(\alpha U_i^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T V_j) V_j \\
& \times (g(\alpha U_i^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T V_j) - R_{ij}) \\
& + (1-\alpha) \sum_{p \in \mathcal{B}(i)} \sum_{j=1}^{n} I_{pj}^{R} g'(\alpha U_p^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(p)} S_{pk} U_k^T V_j) \\
& \times (g(\alpha U_p^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(p)} S_{pk} U_k^T V_j) - R_{pj}) S_{pi} V_j + \lambda_U U_i, \\
\frac{\partial \mathcal{L}}{\partial V_j} = & \sum_{i=1}^{m} I_{ij}^{R} g'(\alpha U_i^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T V_j) \\
& \times (g(\alpha U_i^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T V_j) - R_{ij}) \\
& \times (\alpha U_i + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T) + \lambda_V V_j, \qquad (14)
\end{aligned}
$$

Model based Social Recommender

- **SoReg**

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

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

Information loss: Friends may have diverse tastes!!!

Ma et al. **Recommender Systems with Social Regularization.** *WSDM*, 2011.

Model based Social Recommender

- **SoReg**

Individual-based regularization:
Regularize with friends individually

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

Related Work

	Behavior	Content	Social	Trust
Collaborative filtering (CF) [Herlocker *et al*. TOIS; Koren KDD]	✔			
Content-based filtering with CF [Balabanovic *et al*.; Liu *et al*. CIKM;]	✔	✔		
SoRec [Ma *et al*. CIKM, TIS] SoReg [Ma *et al*. WSDM]	✔		✔	
Trust-based methods [Massa *et al*. RecSys; Jamali *et al*. KDD; Ma *et al*. SIGIR, TIST]	✔			✔

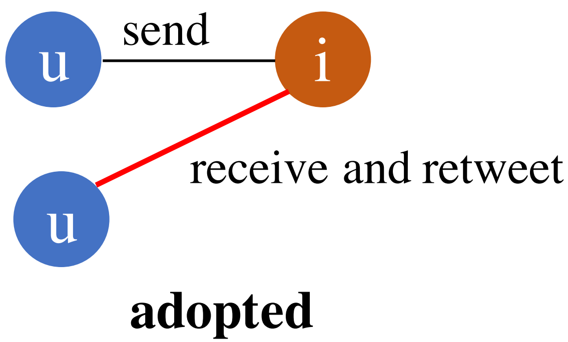
- **Q:** What are the **factors** of users' decisions on retweeting? Can we **observe** them from the data? How to **integrate** the information for accurate prediction?

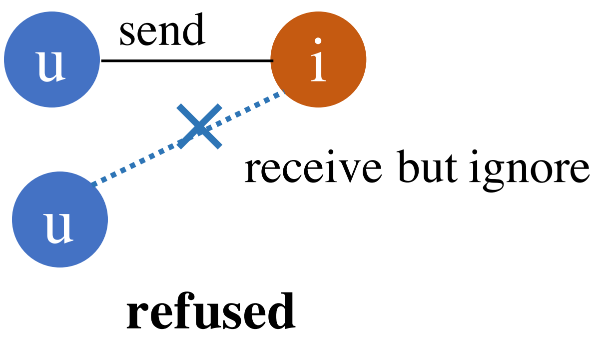
Observation: Social Contextual Factors

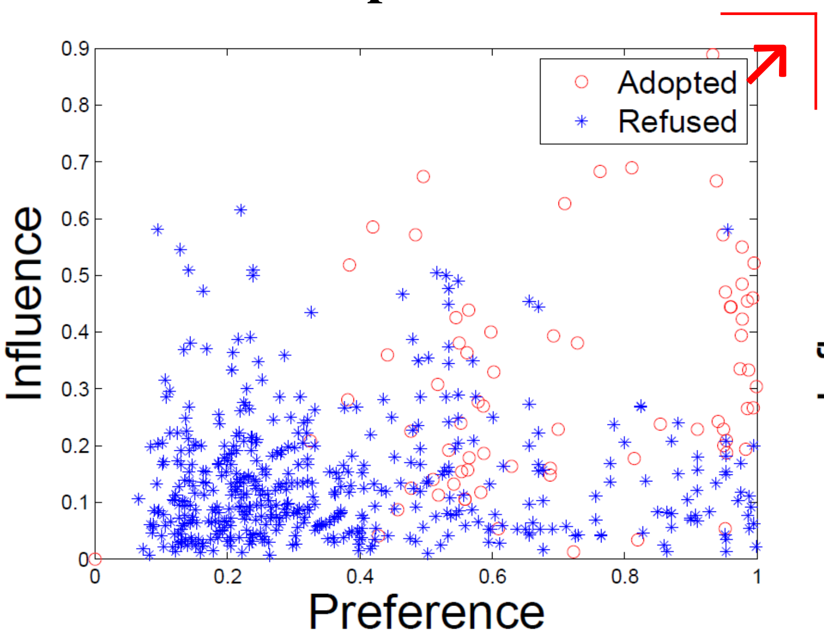
- Will Michelle Obama share this message?
- Please list your reasons.

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

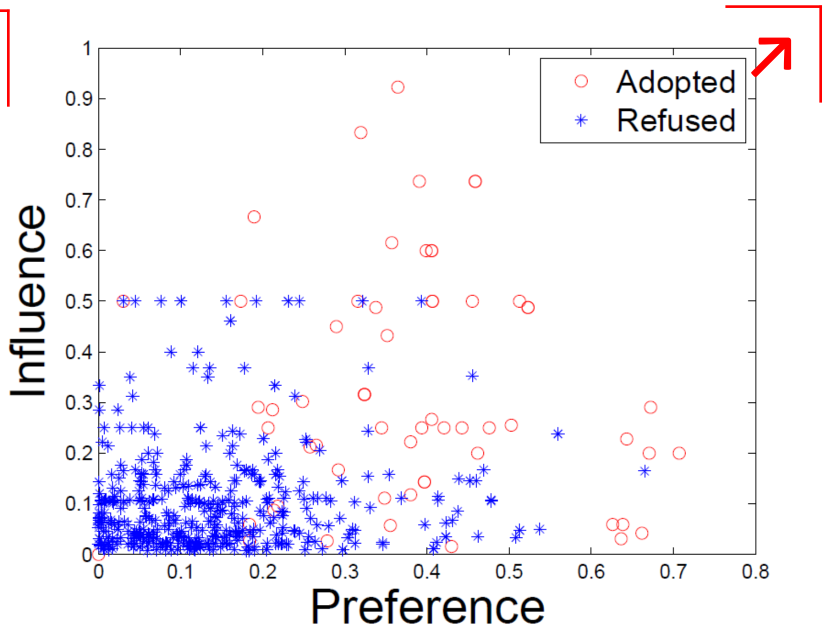
Observation: Social Contextual Factors





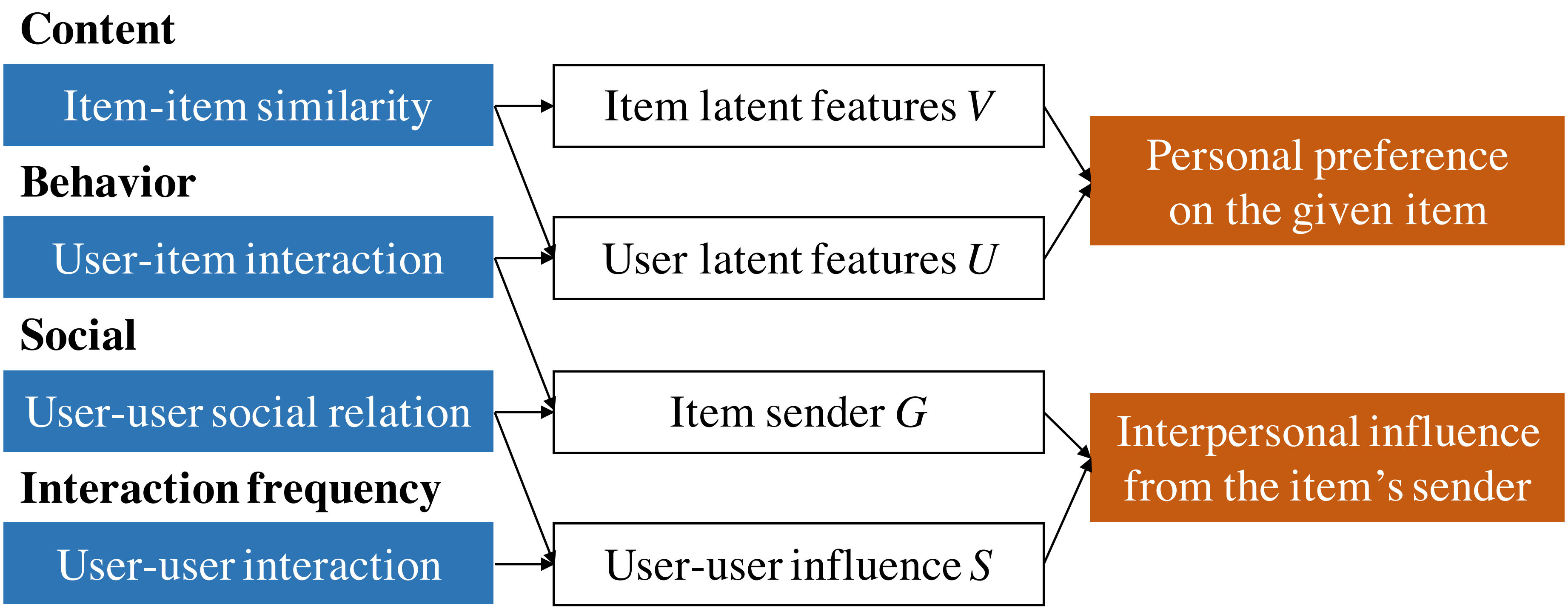


China's Facebook: Renren

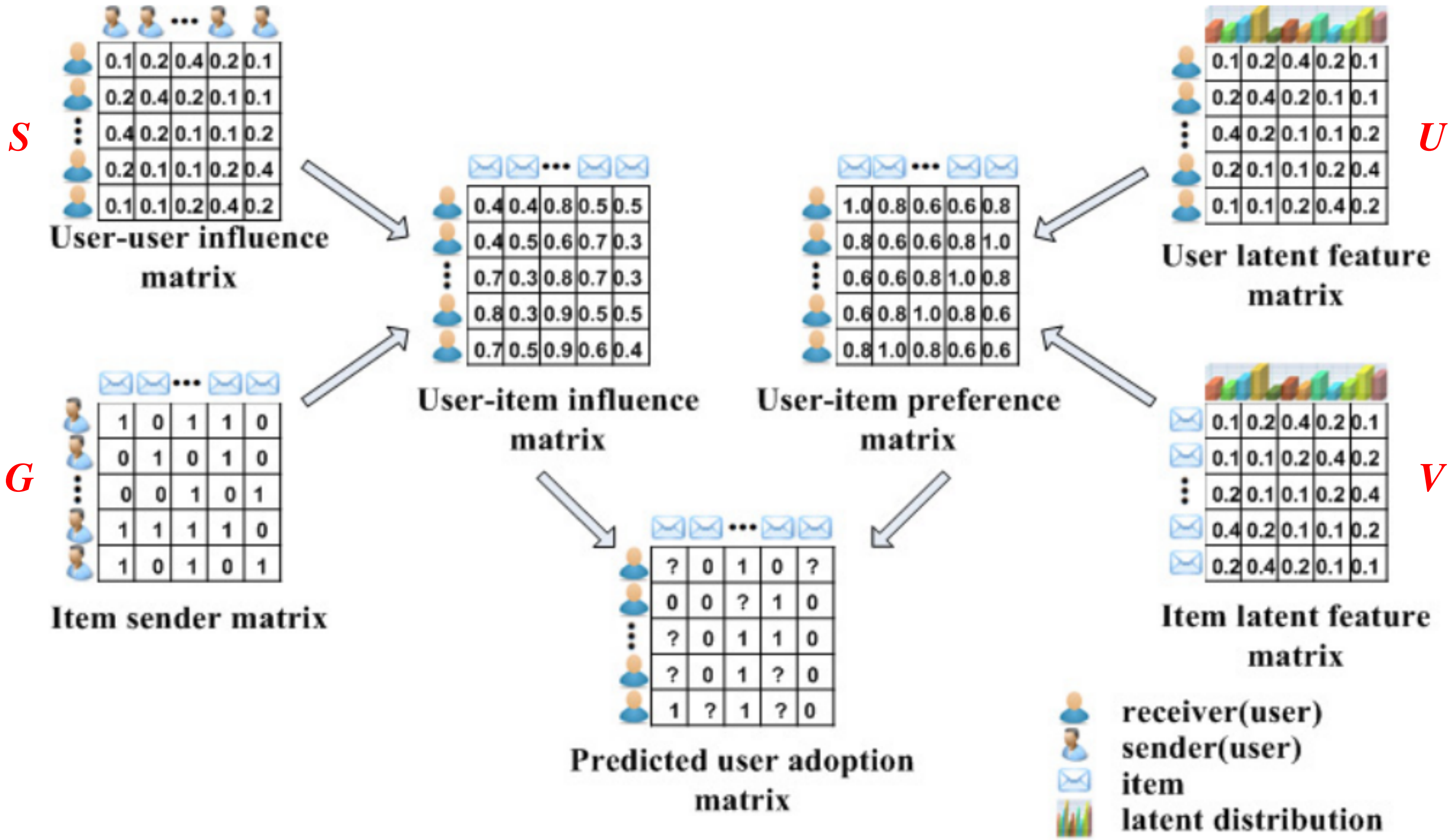


China's Twitter: Tencent Weibo

Representation: From Contextual Information to Contextual Factors



Model: ContextMF



Model: 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

Model: ContextMF

- Gradient descent method

$$
\begin{aligned}
\frac{\partial \mathcal{J}}{\partial \mathbf{S}} &= 2\Big(-\mathbf{R}(\mathbf{G} \odot \mathbf{V}^\top \mathbf{U}) + (\mathbf{S}\mathbf{G}^\top \odot \mathbf{U}^\top \mathbf{V})\mathbf{G} \\
&\quad + \gamma(\mathbf{S} - \mathbf{F}) + \delta \mathbf{S}\Big) \\
\frac{\partial \mathcal{J}}{\partial \mathbf{U}} &= 2\Big(-\mathbf{V}\mathbf{R}^\top + \mathbf{V}(\mathbf{G}\mathbf{S}^\top \odot \mathbf{V}^\top \mathbf{U}) - 2\alpha \mathbf{U}\mathbf{W} \\
&\quad + 2\alpha \mathbf{U}\mathbf{U}^\top \mathbf{U} + \eta \mathbf{U}\Big) \\
\frac{\partial \mathcal{J}}{\partial \mathbf{V}} &= 2\Big(-\mathbf{U}\mathbf{R} + \mathbf{U}(\mathbf{S}\mathbf{G}^\top \odot \mathbf{U}^\top \mathbf{V}) - 2\beta \mathbf{V}\mathbf{C} \\
&\quad + 2\beta \mathbf{V}\mathbf{V}^\top \mathbf{V} + \lambda \mathbf{V}\Big)
\end{aligned}
$$

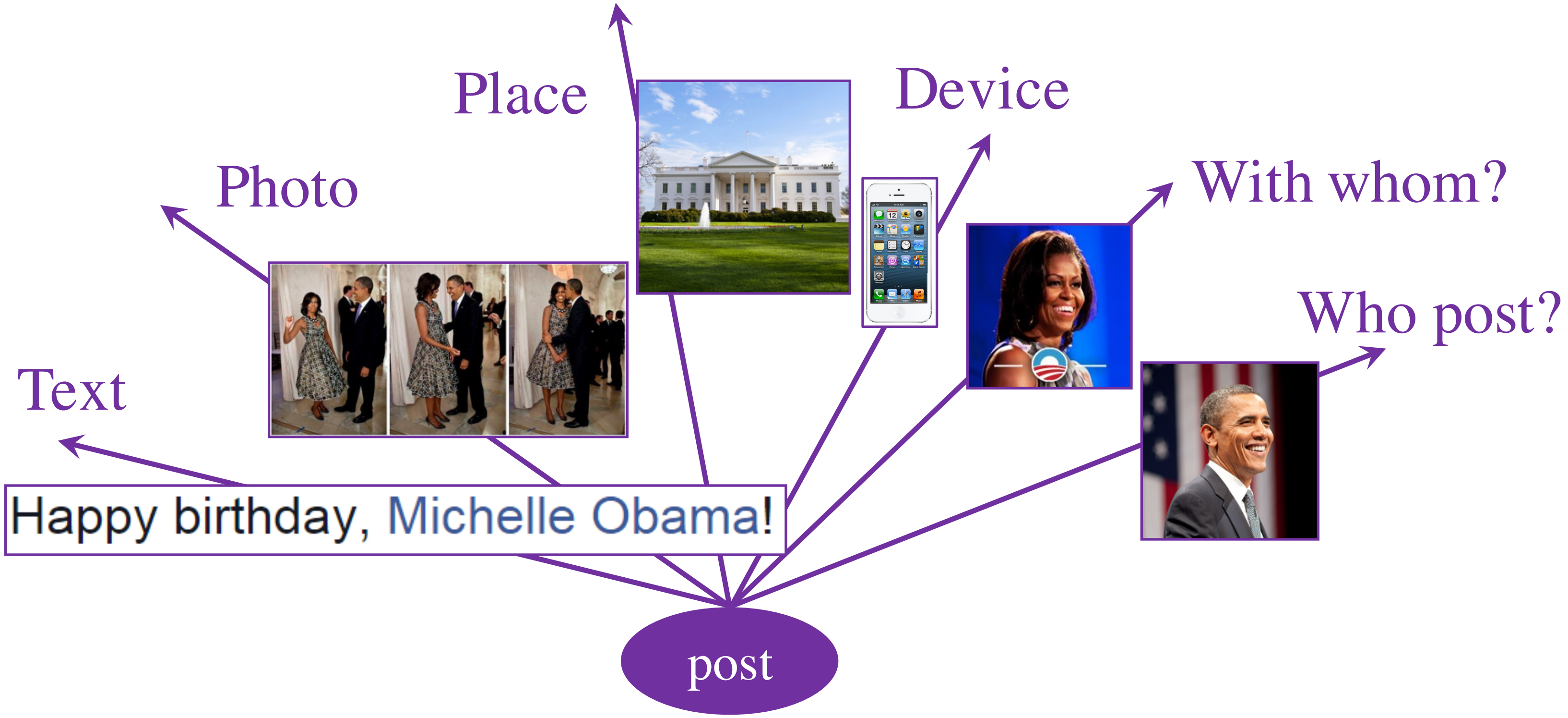
Experimental Results

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**

vs. SoReg [TIST'11]	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%

- **Deployed** in Weibo News Feed. Improved conversion rate from 5.78% to 8.27% (relatively **43%**).
- #citations = **149**

Observation: Spatial Context



Jan. 18
Birthday party
@ White house

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

Observation: Temporal Context

Photo

Text

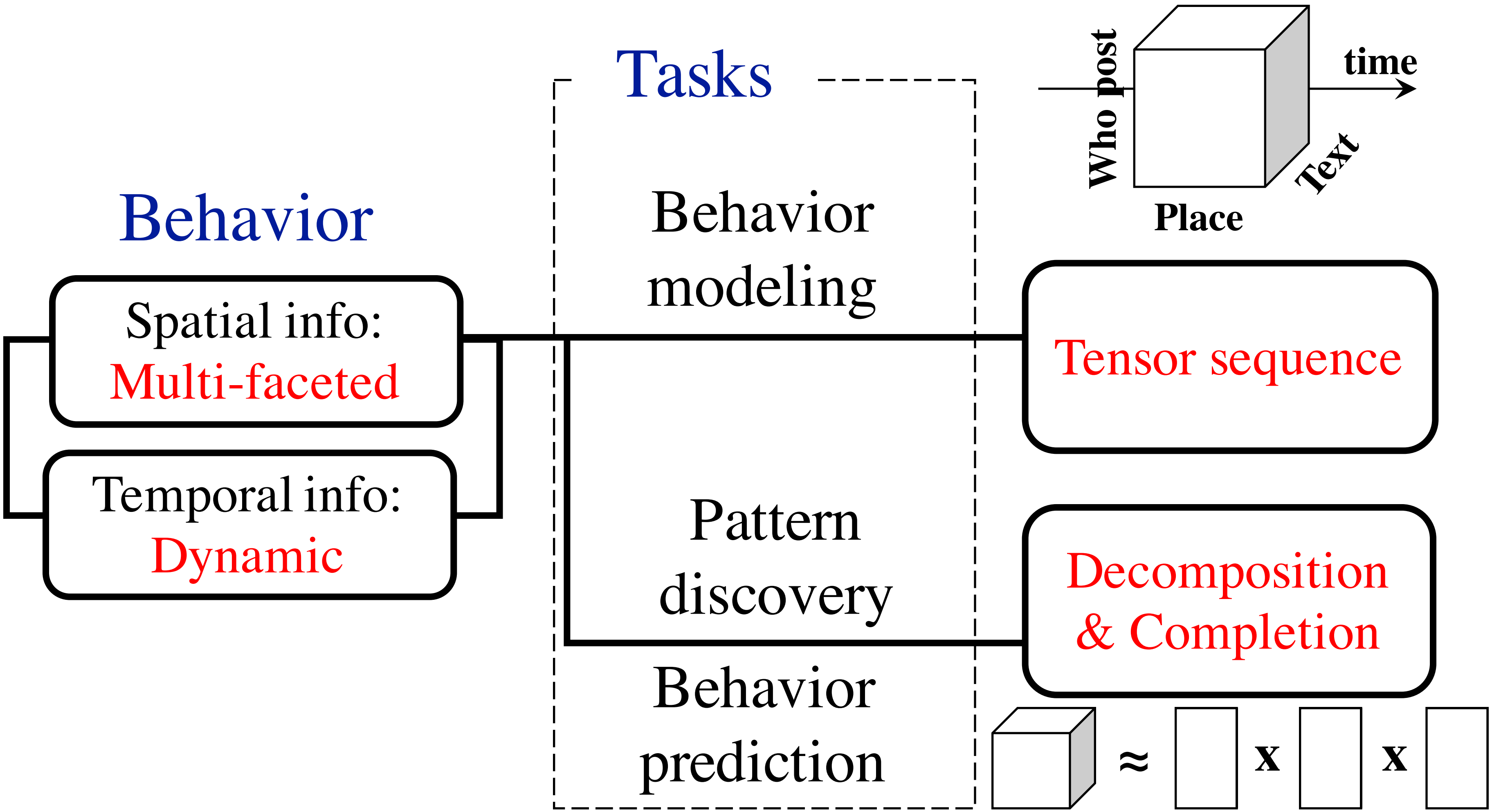
Happy birthday, Michelle Obama!

post → post → time

Jan. 18
Birthday party
@ White house

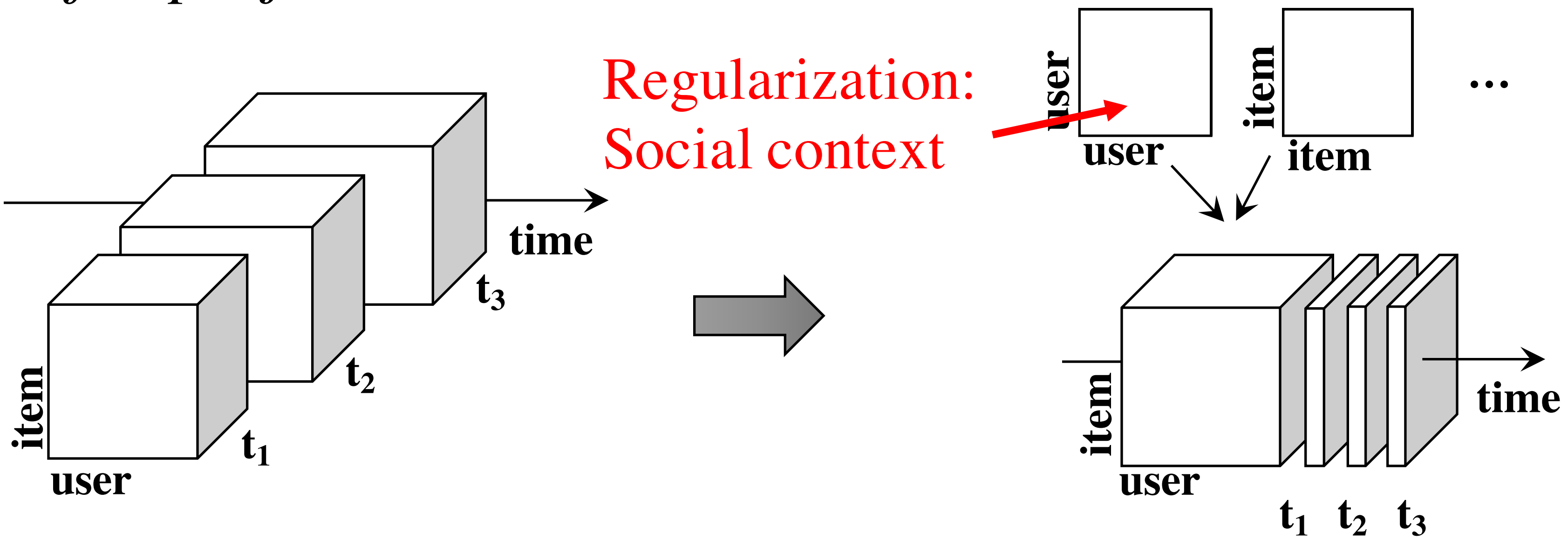
March 17
St. Patrick's Day
@ Bar

Representation: Tensor Sequence



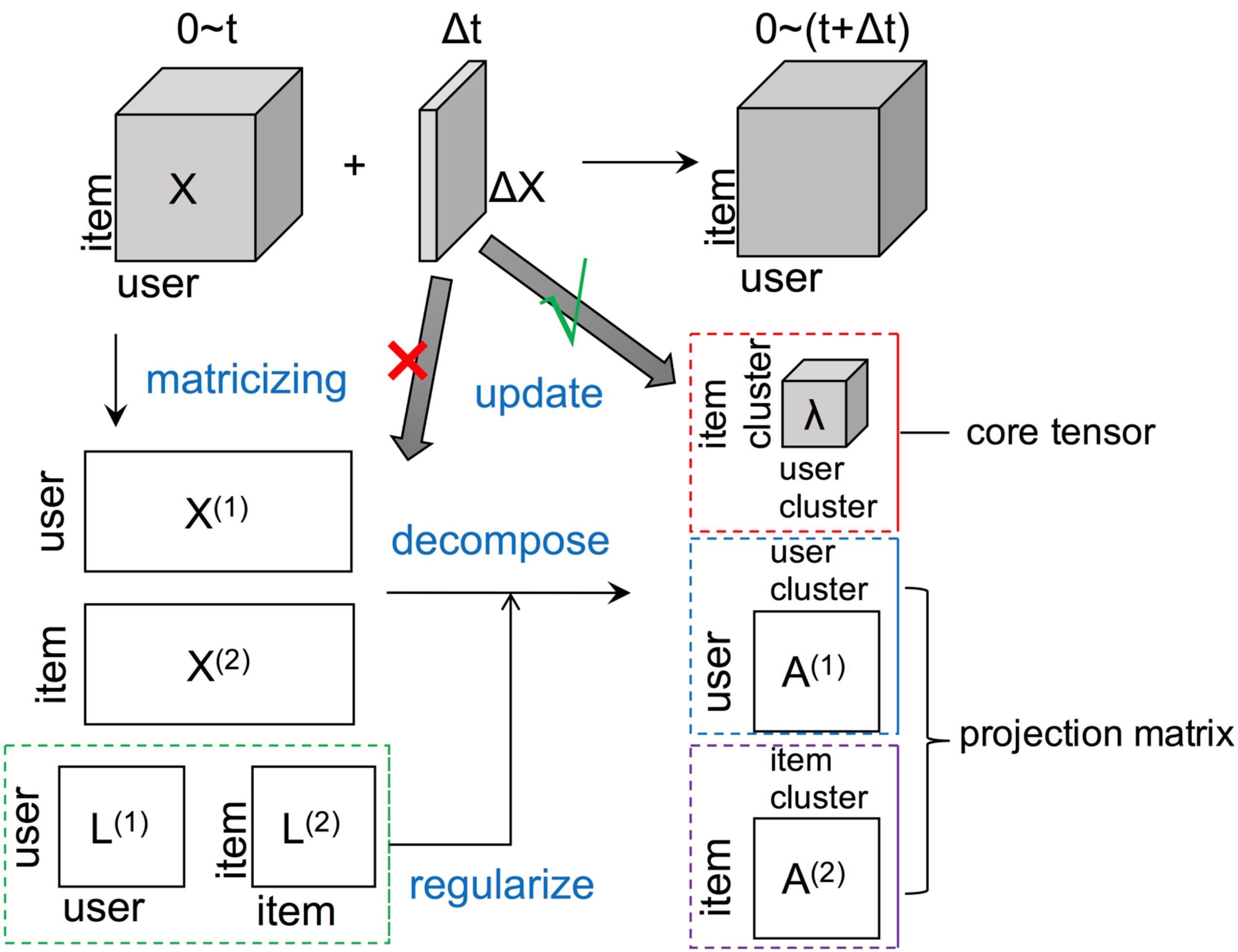
Challenges: Sparsity and Complexity

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



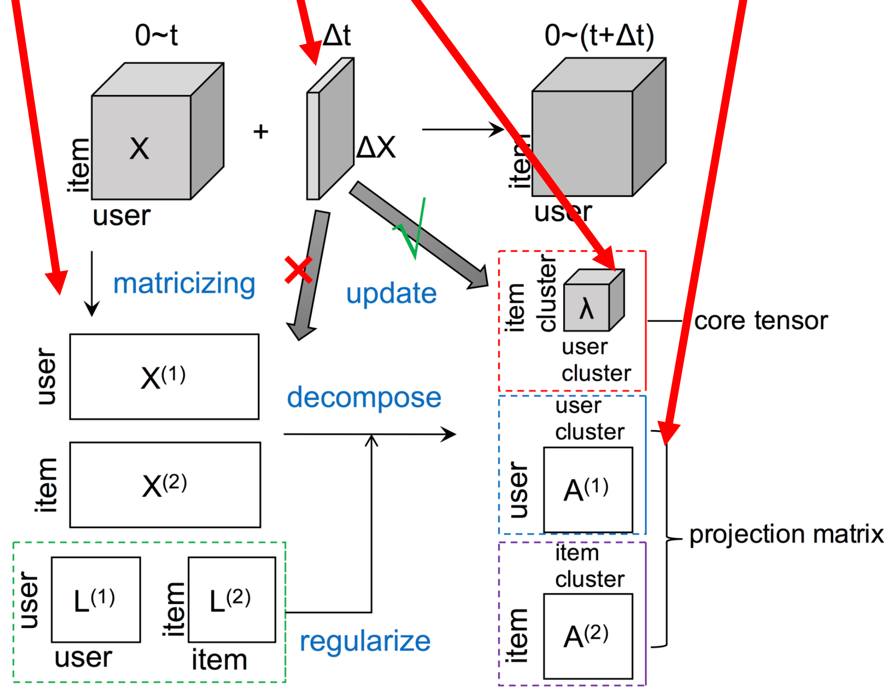
Model: FEMA

Flexible Evolutionary Multi-faceted Analysis



Tensor Perturbation Theory

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



Algorithm: FEMA

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

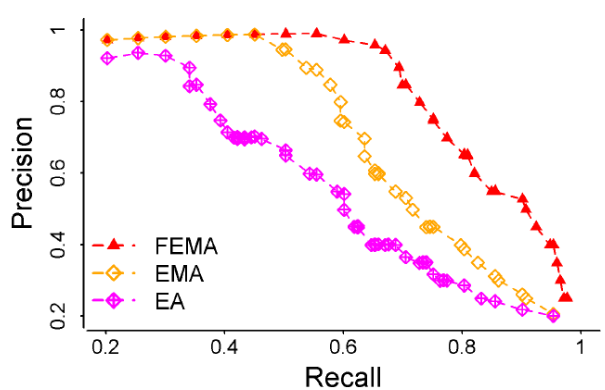
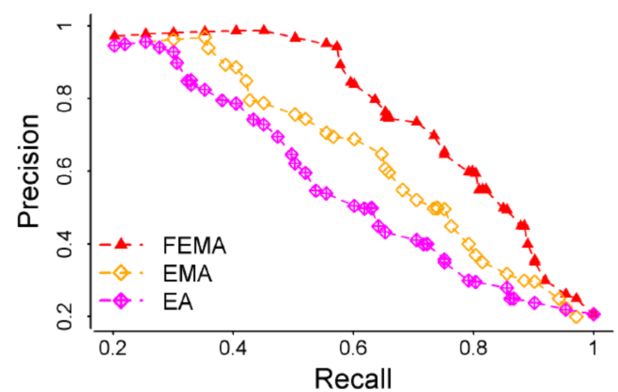
core tensor

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

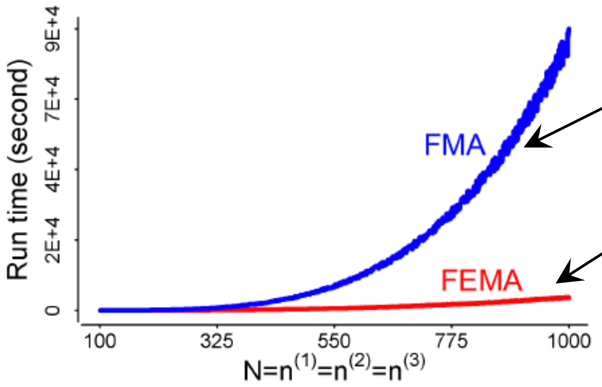
$$|\Delta\mathbf{a}_i^{(m)}| \leq 2\|\Delta\mathbf{X}^{(m)}\|_2\sum_{j\neq i}\frac{(\lambda^{\max}_{\mathbf{X}^{(m)\top}\mathbf{X}^{(m)}})^{\frac{1}{2}}}{|\lambda_i^{(m)} - \lambda_j^{(m)}|}$$

projection matrix

Results: FEMA > EMA > EA

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

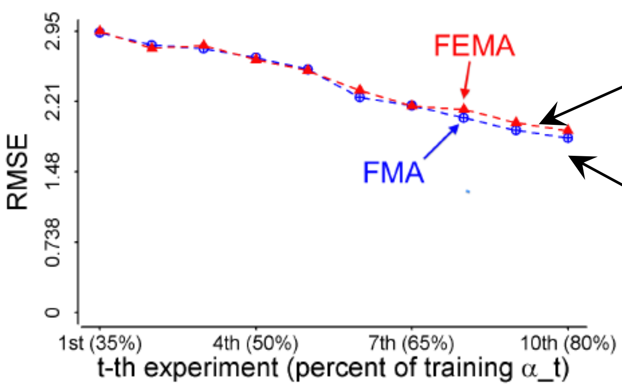
Results: Efficiency



Time vs Num. objects N

Re-decomposition:
Re-compute projection matrices

Evolutionary analysis:
Use ΔX to update λ and a

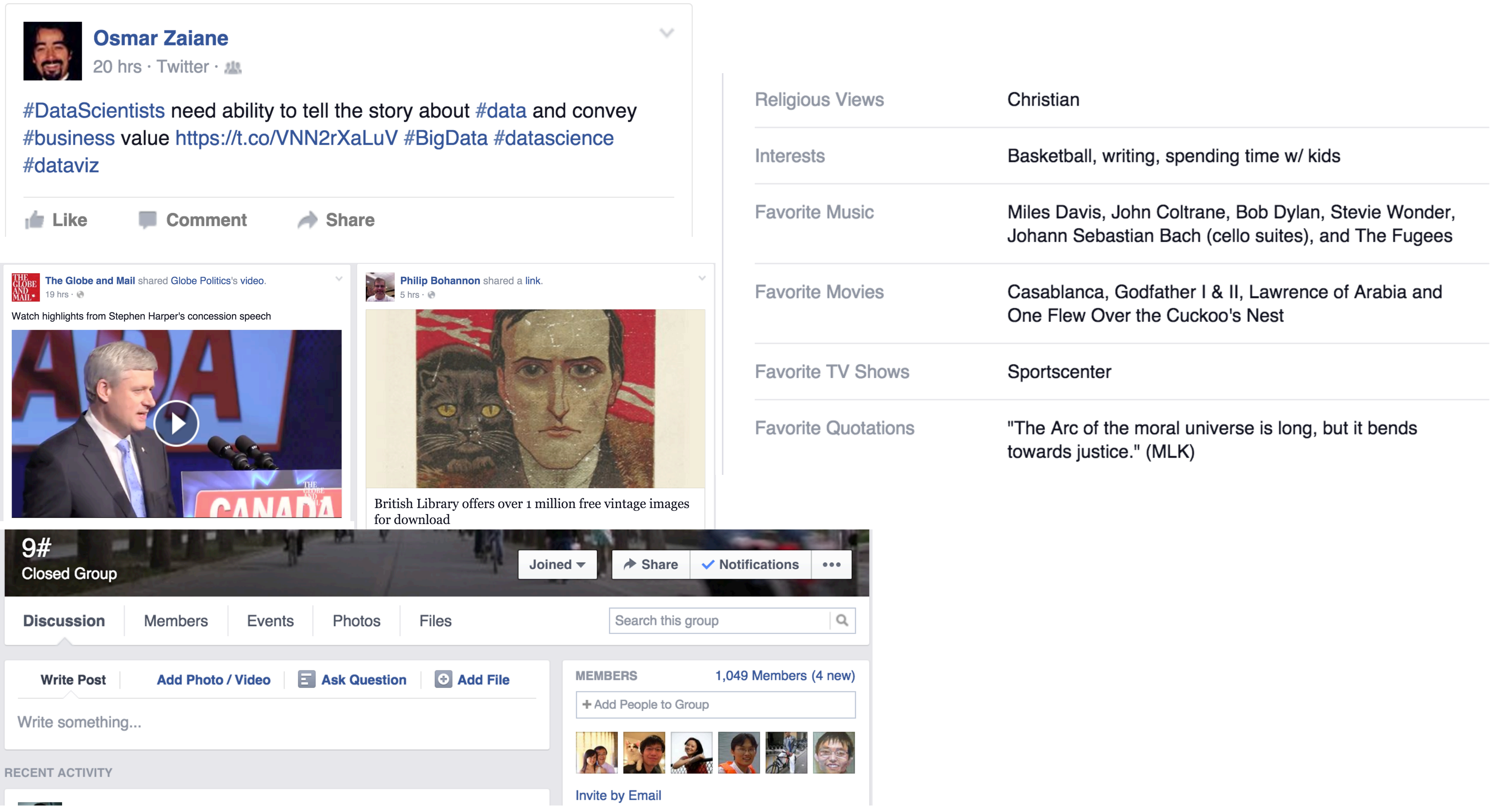


The loss is small.

Evolutionary analysis:
Use ΔX to update λ and a

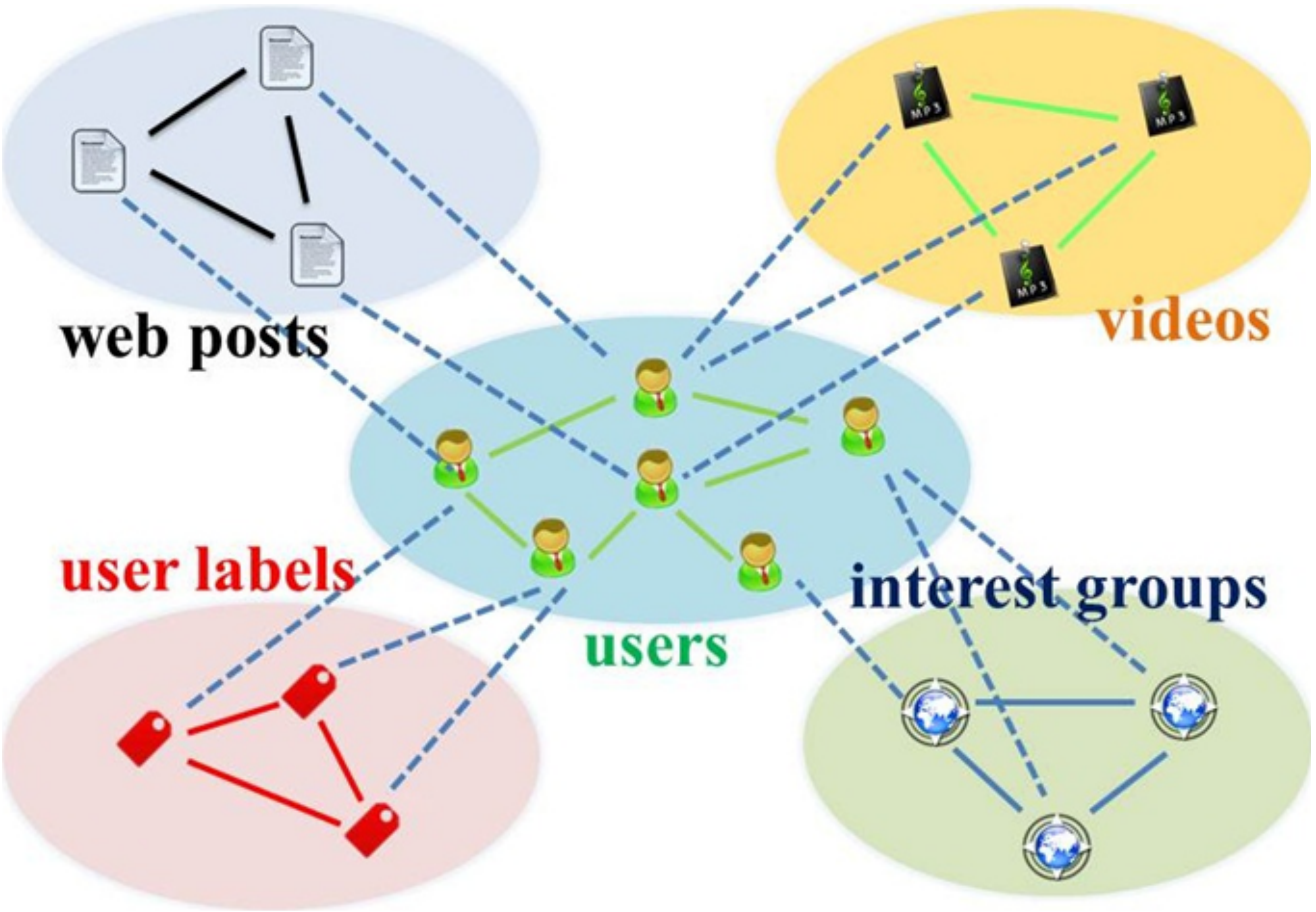
Re-decomposition:
Re-compute projection matrices

Observation: Multiple Domains

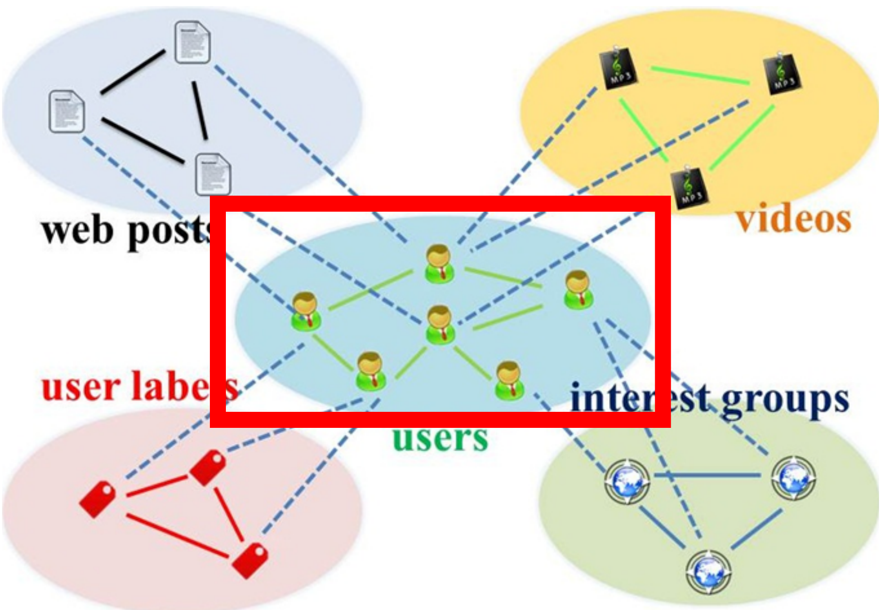


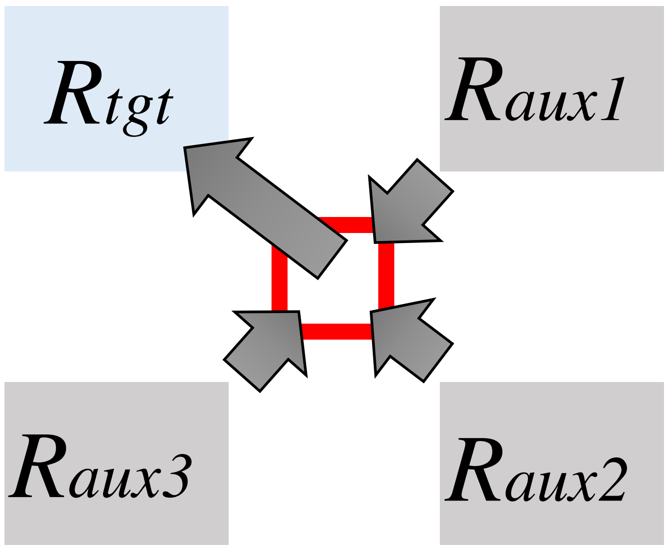
Jiang et al. **Social Recommendation across Multiple Relational Domains.** *CIKM*, 2012.
Social Recommendation with Cross-Domain Transferable Knowledge. *TKDE*, 2015.

Representation: Star-Structured Graph



Representation: Social Bridge

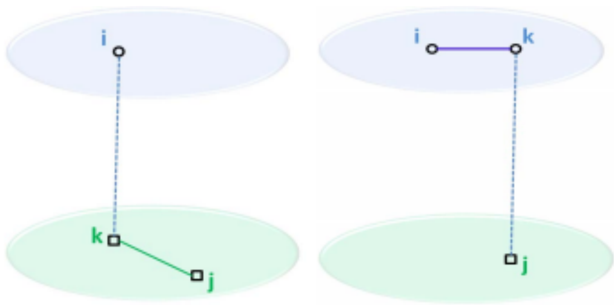




Bridge: Tie strength

Algorithm: Hybrid Random Walk

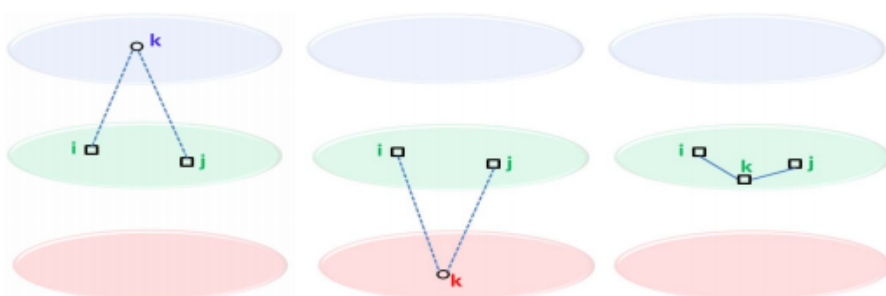
- Updating cross-domain links



(a) Route 1 (b) Route 2

$$p_{ij}^{(\mathcal{UP})^+} = \delta \sum_{u_k \in \mathcal{U}} r_{ik}^{(\mathcal{U})} p_{kj}^{(\mathcal{UP})^+} + (1-\delta) \sum_{p_k \in \mathcal{P}} p_{ik}^{(\mathcal{UP})^+} r_{kj}^{(\mathcal{P})}$$
$$p_{ij}^{(\mathcal{UP})^-} = \delta \sum_{u_k \in \mathcal{U}} r_{ik}^{(\mathcal{U})} p_{kj}^{(\mathcal{UP})^-} + (1-\delta) \sum_{p_k \in \mathcal{P}} p_{ik}^{(\mathcal{UP})^-} r_{kj}^{(\mathcal{P})}$$
$$p_{ij}^{(\mathcal{UT})^+} = \eta \sum_{u_k \in \mathcal{U}} r_{ik}^{(\mathcal{U})} p_{kj}^{(\mathcal{UT})^+} + (1-\eta) \sum_{t_k \in \mathcal{T}} p_{ik}^{(\mathcal{UT})^+} r_{kj}^{(\mathcal{T})}$$
$$\mathbf{P}^{(\mathcal{UP})^+}(t+1) = \delta \mathbf{R}^{(\mathcal{U})}(t)\mathbf{P}^{(\mathcal{UP})^+}(t) + (1-\delta)\mathbf{P}^{(\mathcal{UP})^+}(t)\mathbf{R}^{(\mathcal{P})}$$
$$\mathbf{P}^{(\mathcal{UP})^-}(t+1) = \delta \mathbf{R}^{(\mathcal{U})}(t)\mathbf{P}^{(\mathcal{UP})^-}(t) + (1-\delta)\mathbf{P}^{(\mathcal{UP})^-}(t)\mathbf{R}^{(\mathcal{P})}$$
$$\mathbf{P}^{(\mathcal{UT})^+}(t+1) = \eta \mathbf{R}^{(\mathcal{U})}(t)\mathbf{P}^{(\mathcal{UT})^+}(t) + (1-\eta)\mathbf{P}^{(\mathcal{UT})^+}(t)\mathbf{R}^{(\mathcal{T})}$$

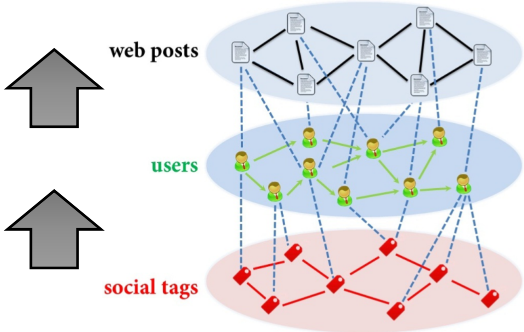
- Updating within-domain links



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

$$r_{ij}^{(\mathcal{U})} = \tau^{(\mathcal{P})}\Big(\mu \sum_{p_k \in \mathcal{P}} p_{ik}^{(\mathcal{UP})^+} p_{jk}^{(\mathcal{UP})^+} + (1-\mu) \sum_{p_k \in \mathcal{P}} p_{ik}^{(\mathcal{UP})^-} p_{jk}^{(\mathcal{UP})^-}\Big)$$
$$+\tau^{(\mathcal{T})} \sum_{t_k \in \mathcal{T}} p_{ik}^{(\mathcal{UT})^+} p_{jk}^{(\mathcal{UT})^+} + \tau^{(\mathcal{U})} \sum_{u_k \in \mathcal{U}} r_{ik}^{(\mathcal{U})} r_{kj}^{(\mathcal{U})} \qquad (12)$$
$$\mathbf{R}^{(\mathcal{U})}(t+1) =$$
$$\tau^{(\mathcal{P})}\Big(\mu \mathbf{P}^{(\mathcal{UP})^+}(t)\mathbf{P}^{(\mathcal{UP})^+}(t)^T + (1-\mu)\mathbf{P}^{(\mathcal{UP})^-}(t)\mathbf{P}^{(\mathcal{UP})^-}(t)^T\Big)$$
$$+\tau^{(\mathcal{T})}\mathbf{P}^{(\mathcal{UT})^+}(t)\mathbf{P}^{(\mathcal{UT})^+}(t)^T + \tau^{(\mathcal{U})}\mathbf{R}^{(\mathcal{U})}(t)\mathbf{R}^{(\mathcal{U})}(t)^T \qquad (13)$$

Results



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

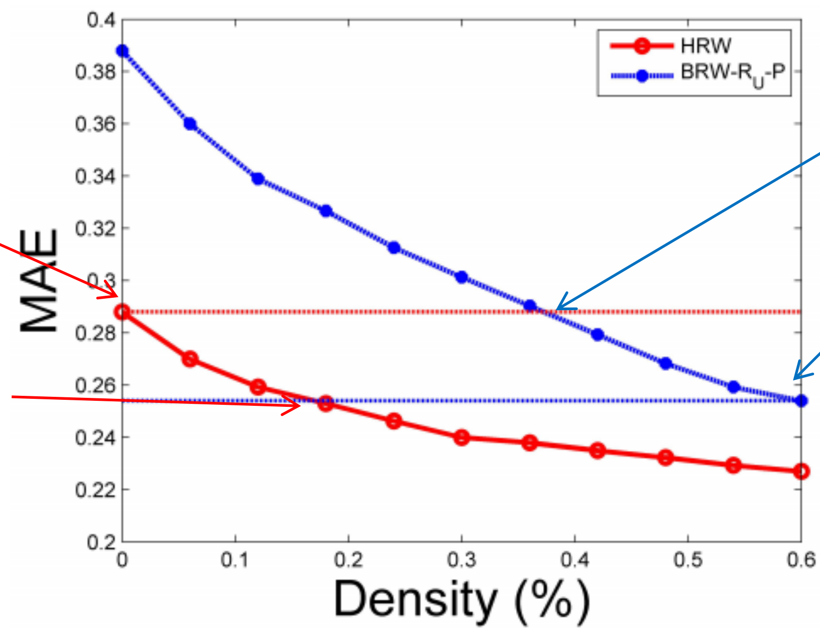
Algorithm	MAE	Precision	Recall	F1	Kendall's $\hat{\tau}$
HRW	**0.227±1.5e-3**	**0.711±1.3e-3**	0.921±1.4e-3	**0.802±1.1e-3**	**0.792±2.5e-3**
BRW-R_U-P (TrustWalker) [10]	0.276±1.1e-3	0.657±7.6e-4	0.935±9.8e-4	0.772±7.6e-4	0.774±1.6e-3
BRW-W_U (ItemRank) [8]	0.318±1.4e-3	0.671±1.5e-3	0.713±2.4e-3	0.691±1.2e-3	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

Results: Insight

- 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

Observation: Multiple Platforms

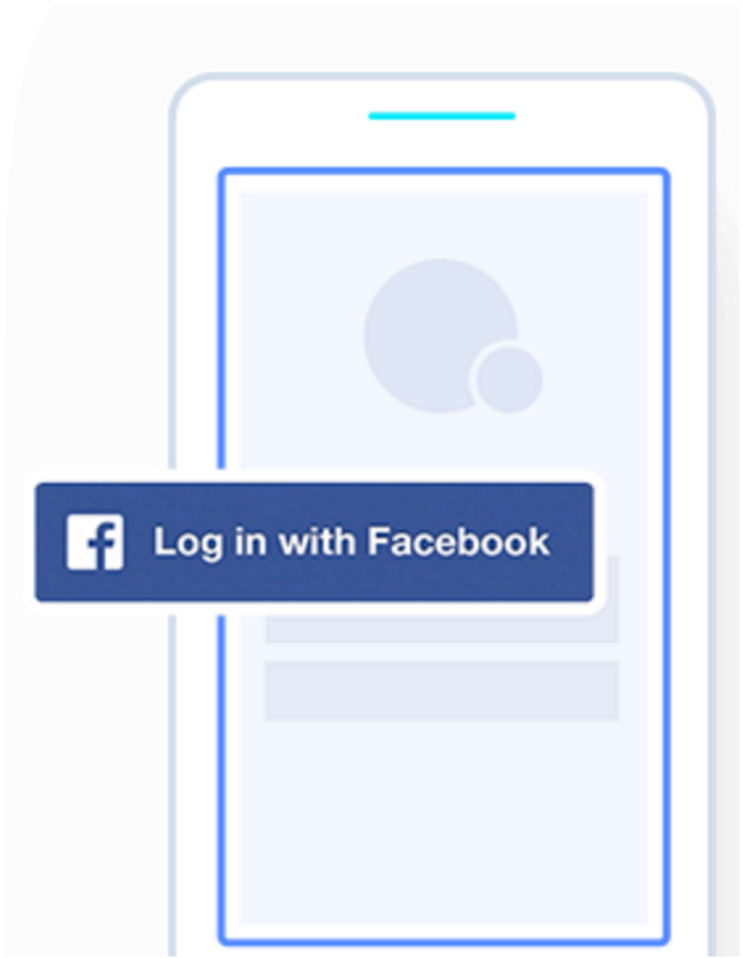
Jiang et al. **Little is Much: Bridging Cross-Platform Behaviors through Overlapped Crowds.** *AAAI*, 2016.

Observation: Cross-Platform

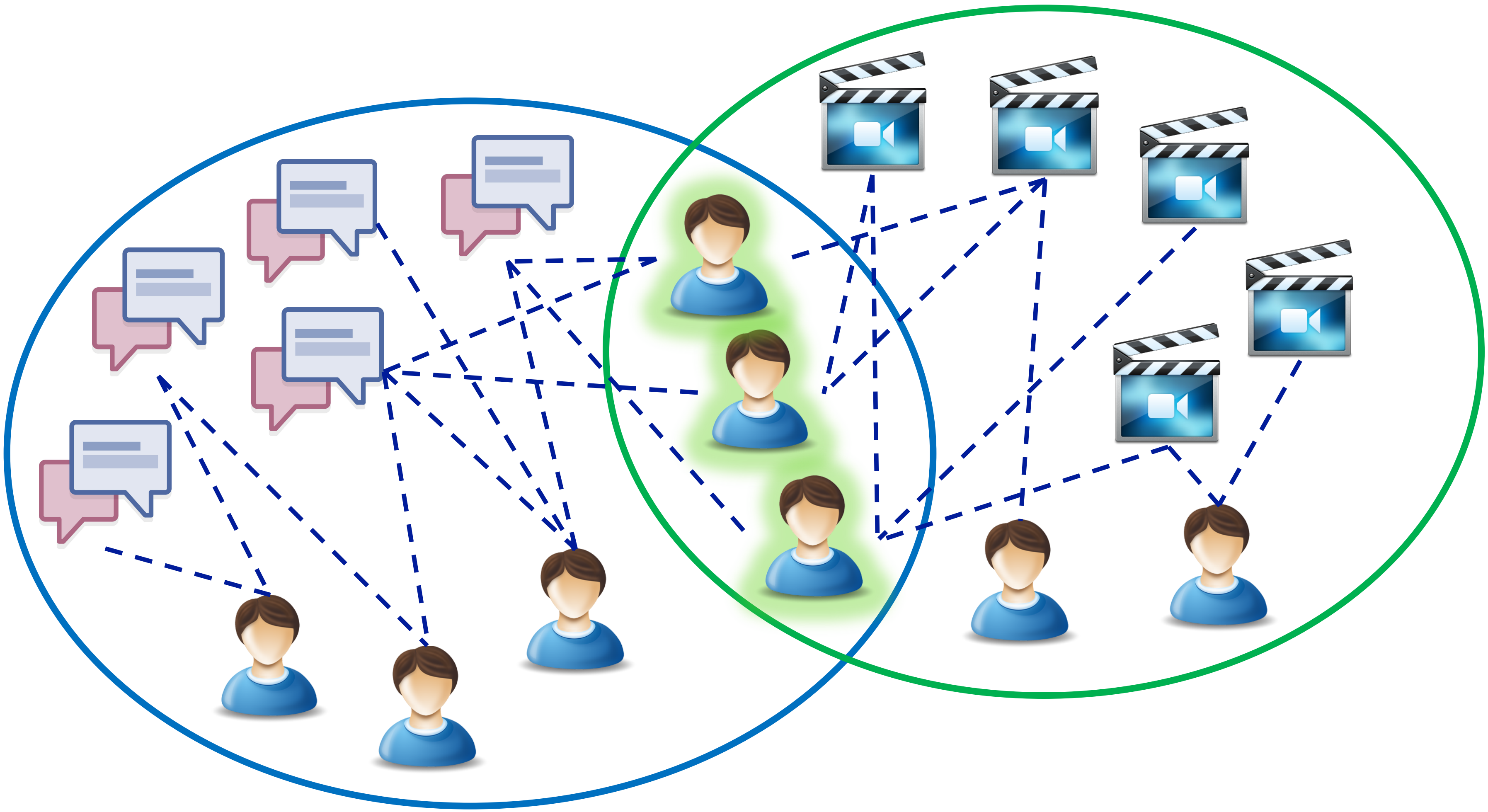
Add Facebook Login to Your App or Website

Facebook Login for Apps is a secure, fast and convenient way for people to log into your app or website.

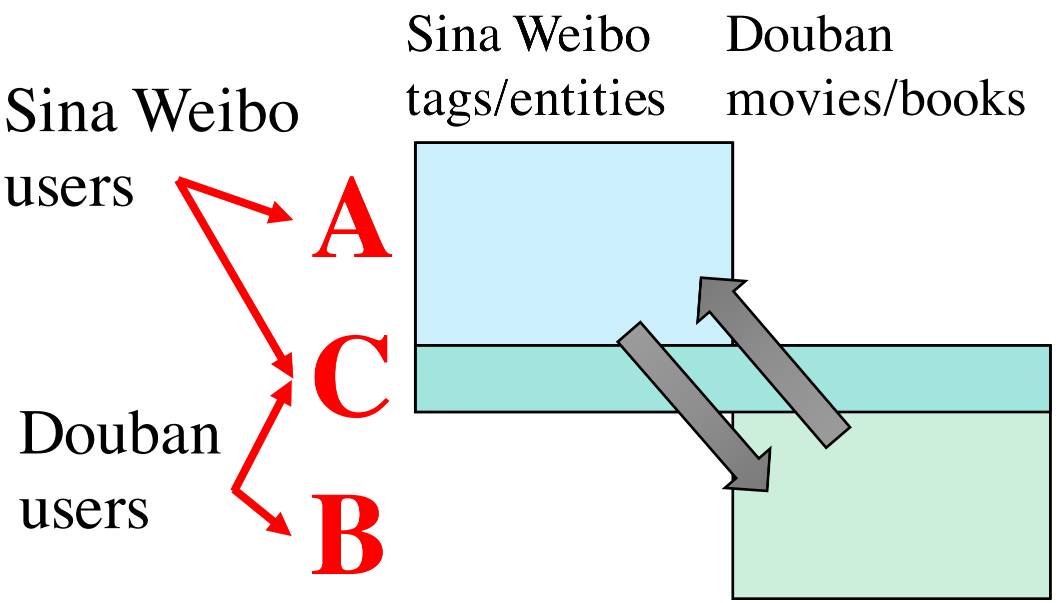
- iOS
- Android
- Websites or mobile websites
- More platforms

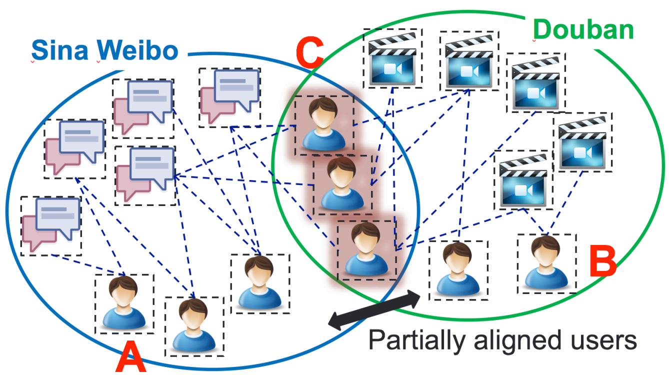


Observation: Partially Overlapped Crowds



Representation: When NO Transfer

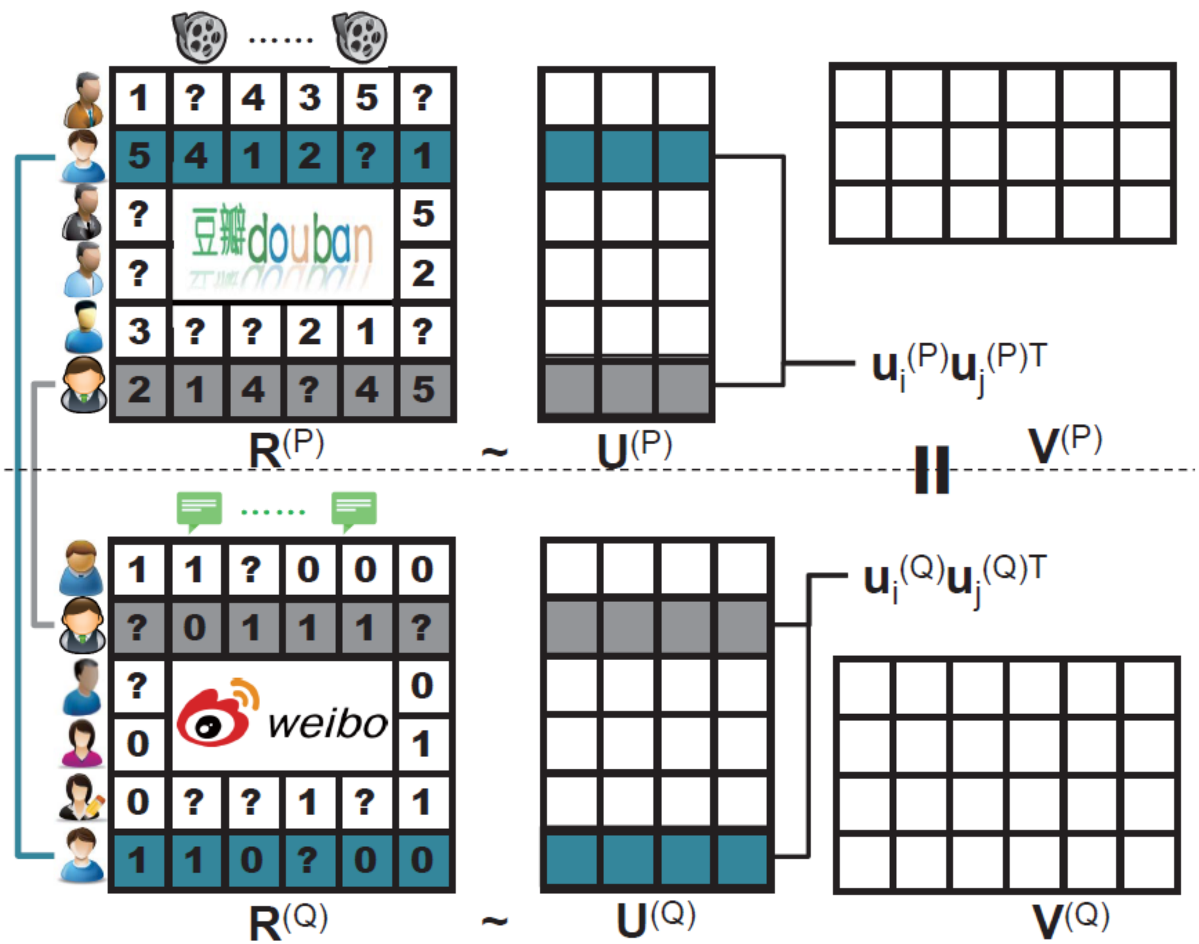




User set	Weibo tweet entity to Douban movie	
	RMSE	MAP
A	Auxiliary platform data!	
C	**0.779**	**0.805**
B	1.439	0.640

User set	Douban book to Weibo social tag	
	RMSE	MAP
A	0.429	0.464
C	**0.267**	**0.666**
B	Auxiliary platform data!	

Algorithm: XPTrans



Algorithm: XPTrans

- Input
  - Tgt./Aux. platform P/Q;
  - Behavior data R(P)/R(Q);
  - Observation W(P)/W(Q);
  - Overlapping indicator W(P,Q),
- Output
  - User latent representation U(P)/U(Q);
  - Item latent representation V(P)/V(Q);
  - Missing values in R(P)

- Objective function

Target platform

Auxiliary platform

$$\mathcal{J} = \sum_{i,j} W_{i,j}^{(P)} \left(R_{i,j}^{(P)} - \sum_{r} U_{i,r}^{(P)} V_{r,j}^{(P)} \right)^2 + \lambda \sum_{i,j} W_{i,j}^{(Q)} \left(R_{i,j}^{(Q)} - \sum_{r} U_{i,r}^{(Q)} V_{r,j}^{(Q)} \right)^2 + \mu \sum_{i_1,j_1,i_2,j_2} W_{i_1,j_1}^{(P,Q)} W_{i_2,j_2}^{(P,Q)} \left(A_{i_1,i_2}^{(P)} - A_{j_1,j_2}^{(Q)} \right)^2$$

Overlapping user similarity
(Pair-wise regularization)

Results: Leveraging Auxiliary Platform Data

NO Transfer

User set	Weibo tweet entity to Douban movie	
	RMSE	MAP
A	Auxiliary platform data!	
C	0.779	0.805
B	**1.439**	**0.640**

User set	Douban book to Weibo social tag	
	RMSE	MAP
A	**0.429**	**0.464**
C	0.267	0.666
B	Auxiliary platform data!	

Transfer via the Same Latent Space

User set	Weibo tweet entity to Douban movie	
	RMSE	MAP
A		
C	0.757	0.811
B	**1.164 (-19%)**	**0.702 (+9.7%)**

User set	Douban book to Weibo social tag	
	RMSE	MAP
A	**0.411 (-4.2%)**	**0.487 (+5.0%)**
C	0.256	0.681
B		

Results: Leveraging Different Latent Spaces

Transfer via the Same Latent Space

User set	Weibo tweet entity to Douban movie	
	RMSE	MAP
A		
C	0.757	0.811
B	**1.164**	**0.702**

User set	Douban book to Weibo social tag	
	RMSE	MAP
A	**0.411**	**0.487**
C	0.256	0.681
B		

Transfer via Different Latent Spaces

User set	Weibo tweet entity to Douban movie	
	RMSE	MAP
A		
C	0.715	0.821
B	**0.722 (-38%)**	**0.820 (+17%)**

User set	Douban book to Weibo social tag	
	RMSE	MAP
A	**0.374 (-11%)**	**0.533 (+12%)**
C	0.236	0.705
B		

Results: Where Amazing Happens

NO Transfer

User set	Weibo tweet entity to Douban movie	
	RMSE	MAP
A	Auxiliary platform data!	
C	0.779	0.805
B	**1.439**	**0.640**

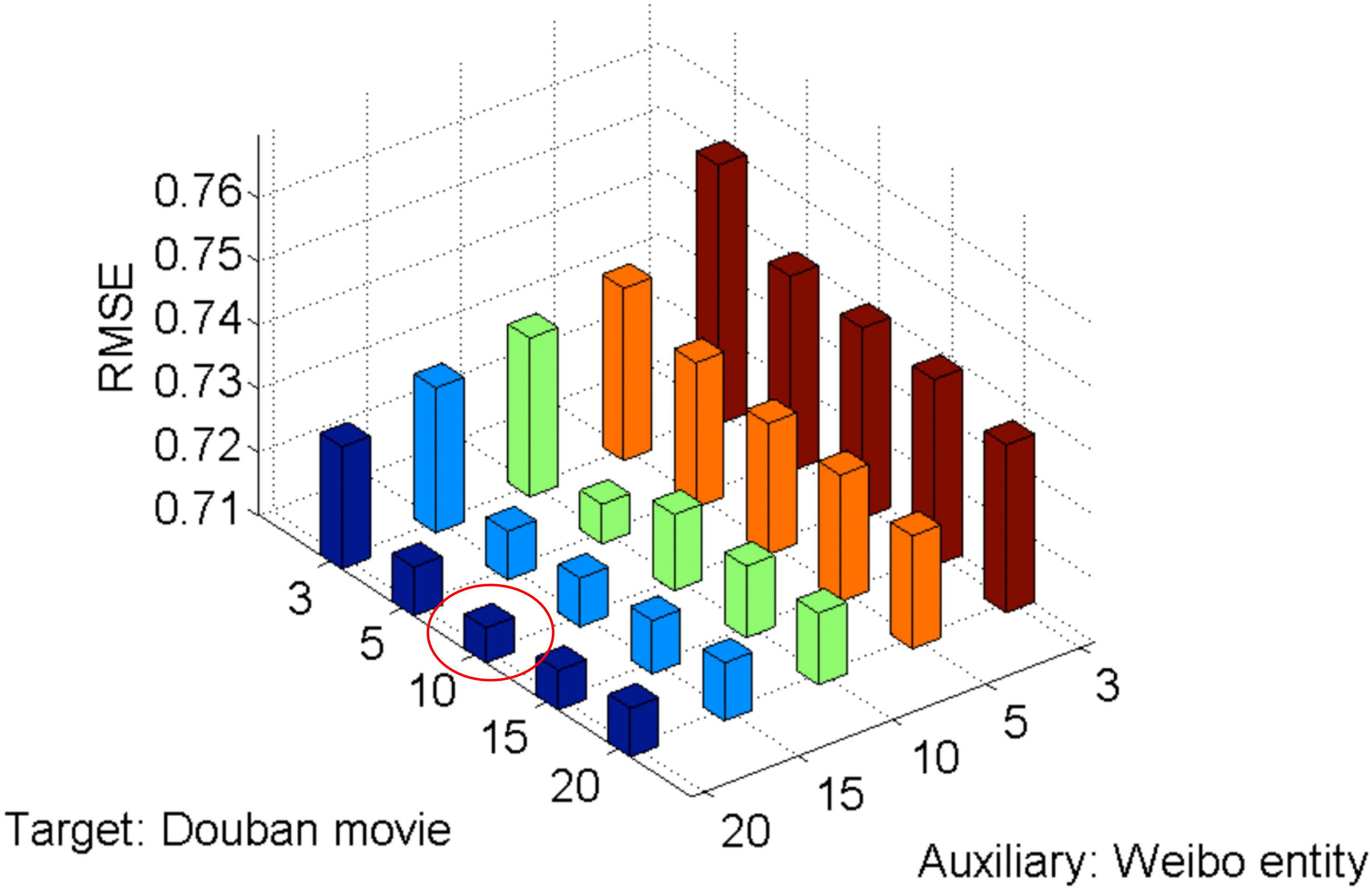
User set	Douban book to Weibo social tag	
	RMSE	MAP
A	**0.429**	**0.464**
C	0.267	0.666
B	Auxiliary platform data!	

Transfer via Different Latent Spaces

User set	Weibo tweet entity to Douban movie	
	RMSE	MAP
A		
C	0.715	0.821
B	**0.722**	**0.820**

User set	Douban book to Weibo social tag	
	RMSE	MAP
A	**0.374**	**0.533**
C	0.236	0.705
B		

Results: Different Sizes of Latent Spaces



Summary

- Like, Reply, Share, Retweet, Favorite, Comment …
- Memory based social recommenders
    - TidalTrust, MoleTrust, TrustWalker
- Model based social recommenders
    - SoRec, "Social Trust" Ensemble, SoReg
- **Observations, Representations, Models**
    - **ContextMF:** Social contexts (preference & influence)
    - **FEMA:** Spatiotemporal contexts (multidimensional)
    - **HybridRW:** Cross-domain behavior modeling
    - **XPTrans:** Cross-platform behavior modeling

Acknowledgement

NSF
NSFC National Natural Science Foundation of China
Tsinghua University 1911
Carnegie Mellon University
University of Maryland 1856
Microsoft Research 微软亚洲研究院
Tencent 腾讯

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Thank you!

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