Data-Driven Behavioral Analytics:

Observations, Representations and Algorithms for ***Prediction and Recommendation***

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ILLINOIS
1867
UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN

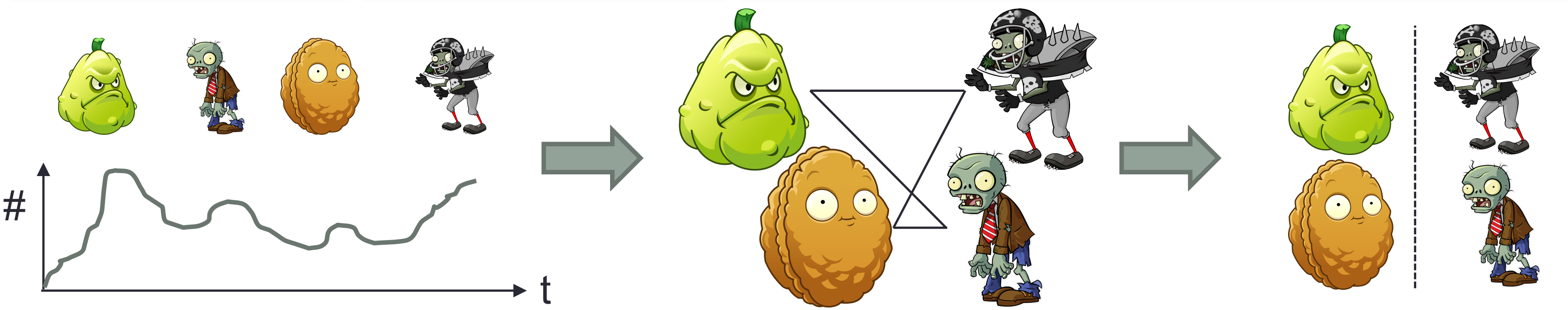
Behavior

❖ **Human behavior** refers to the ***array of every physical action*** … associated with ***individuals***, as well as the ***human race*** as a whole. (From Wikipedia)

Behavioral Analytics

Methodology

Understanding	Observations	Who, what, where, when, why, how… (scientific view)
Modeling	Representations	Graph, network, matrix, tensor… (mathematical view)
Intervening	Algorithms	Classification, prediction, recommendation, anomaly detection… (application view)



Behavioral Analytics/Modeling

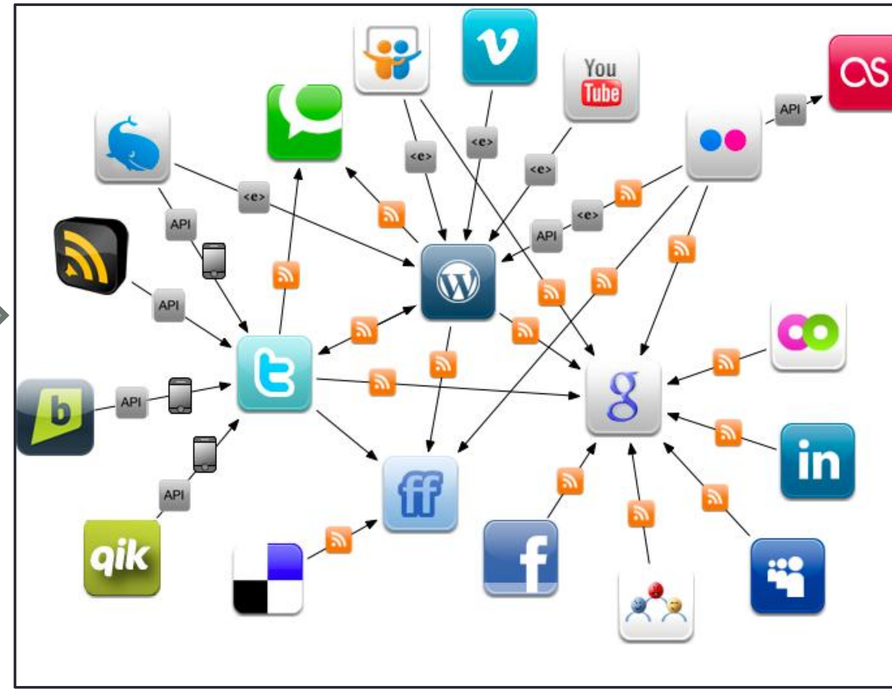
Basic Research Areas

- Six Disruptive Basic Research Areas
  - Engineered Materials (metamaterials and plasmonics)
  - Quantum Information and Control
  - Cognitive Neuroscience
  - Nanoscience and Nanoengineering
  - Synthetic Biology
  - Computational Modeling of Human and Social Behavior

From Experience-Driven to Data-Driven

Physical World

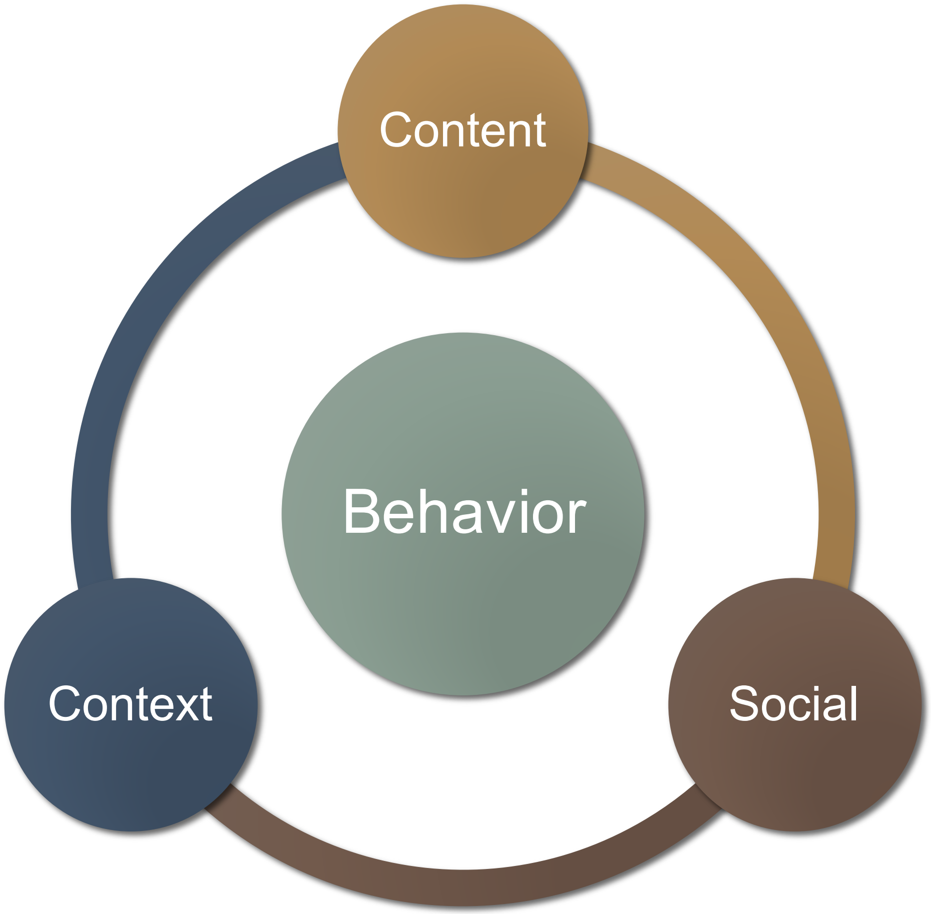
Online Behavioral Data



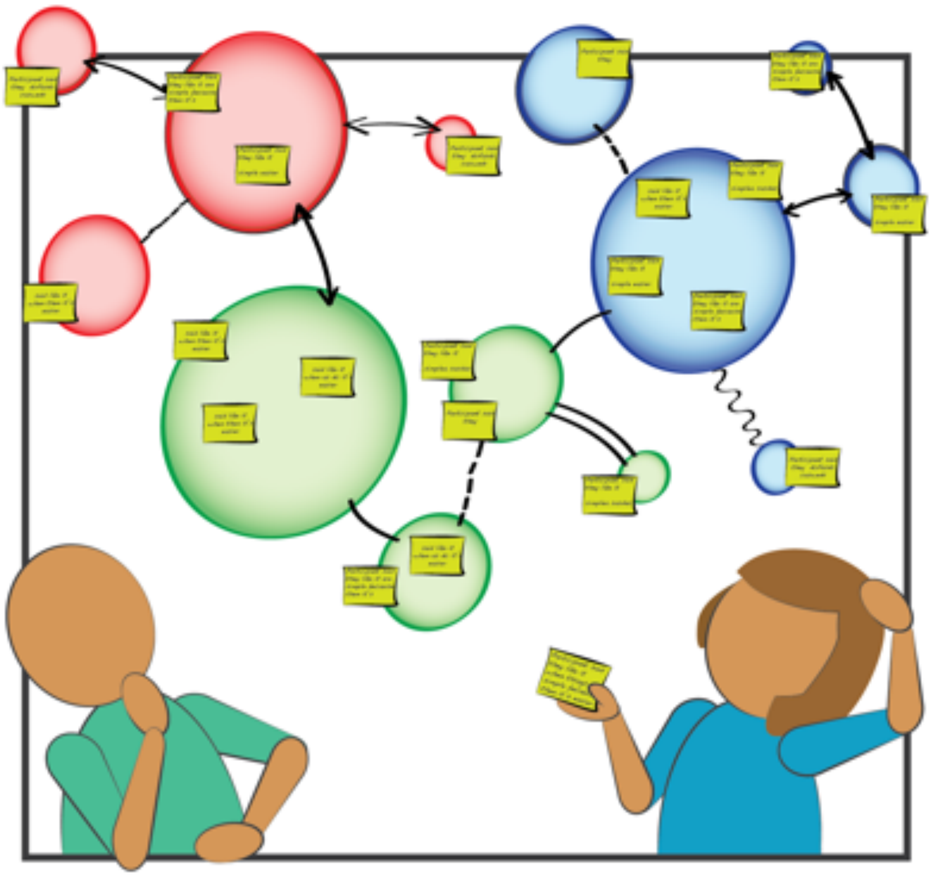
The human behaviors are broadly and deeply recorded in an unprecedented level.

This is the first time that we can get insights of human behaviors and the society from large scale real data.

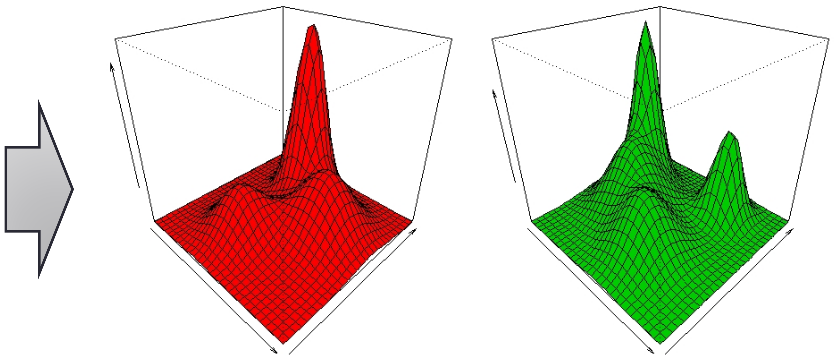
Behaviors are Complex



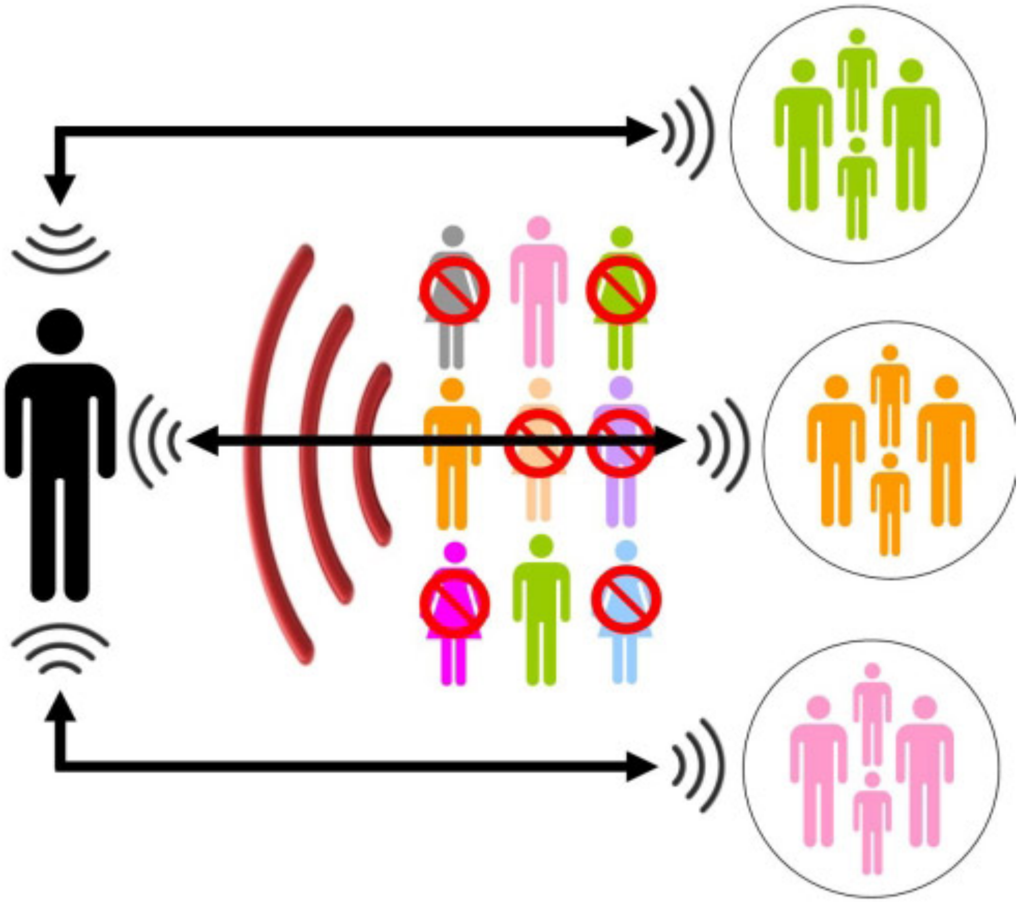
Content Related



Preference is
an important driving factor
for behavior modeling.



Social Related

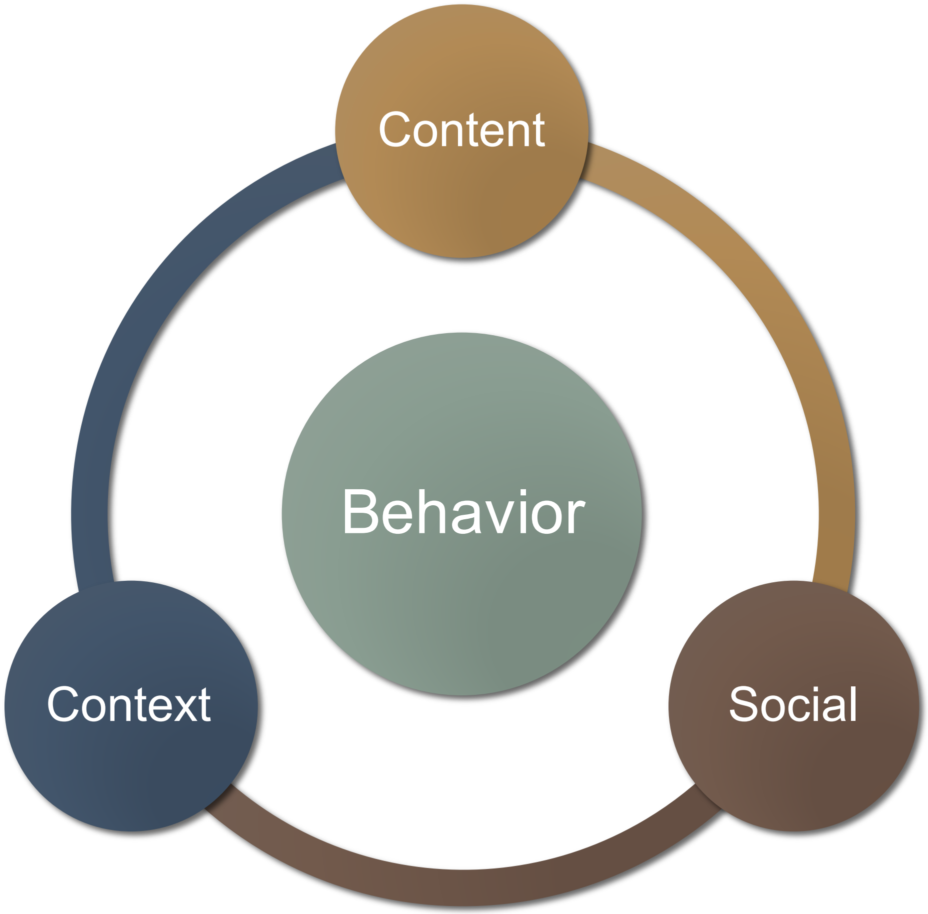


Human behaviors
are highly dependent on
social peers.

Context Related

Rich contextual information: time (when), location (where), channel (how)…

Modeling Complex Behavior



- Understand single factors
- Understand their couplings
- Unify them for prediction and recommendation

Roadmap

- Context
  - W1: Modeling social contexts (CIKM’12, TKDE’14, 129 citations) – online environment (mechanism)
  - W2: Modeling spatiotemporal contexts (KDD’14, 10 citations) – physical environment
- Source
  - W3: Modeling cross-domain behaviors (CIKM’12, TKDE’15, 47 citations)
  - W4: Modeling cross-platform behaviors (AAAI’16)

Roadmap

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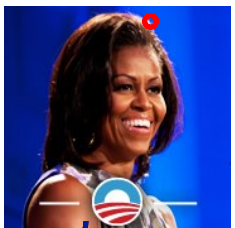
Observation: Social Network Mechanism

Birthday –
NOT politic issues

From my husband –
NOT fans/followers



(0) follow

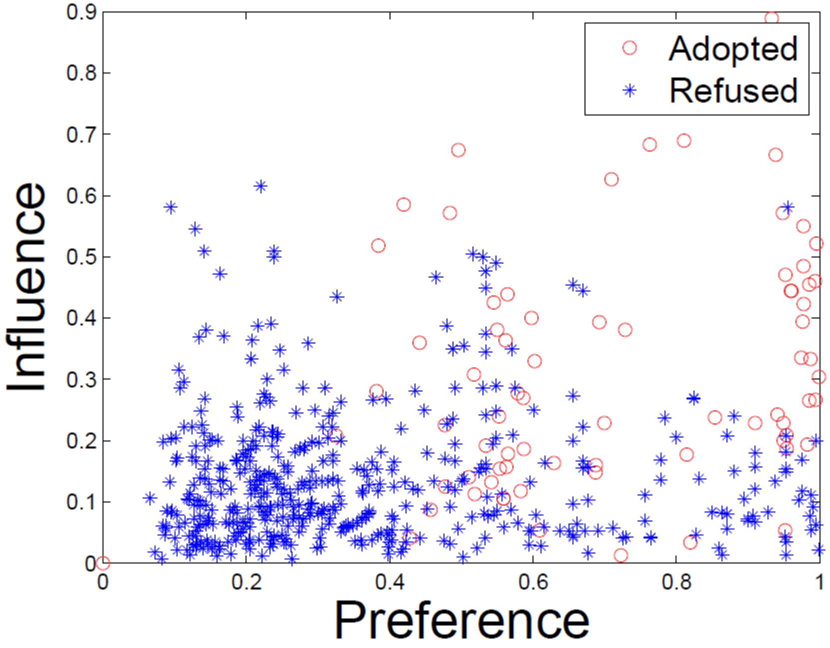
(2) receive & read

(1) post

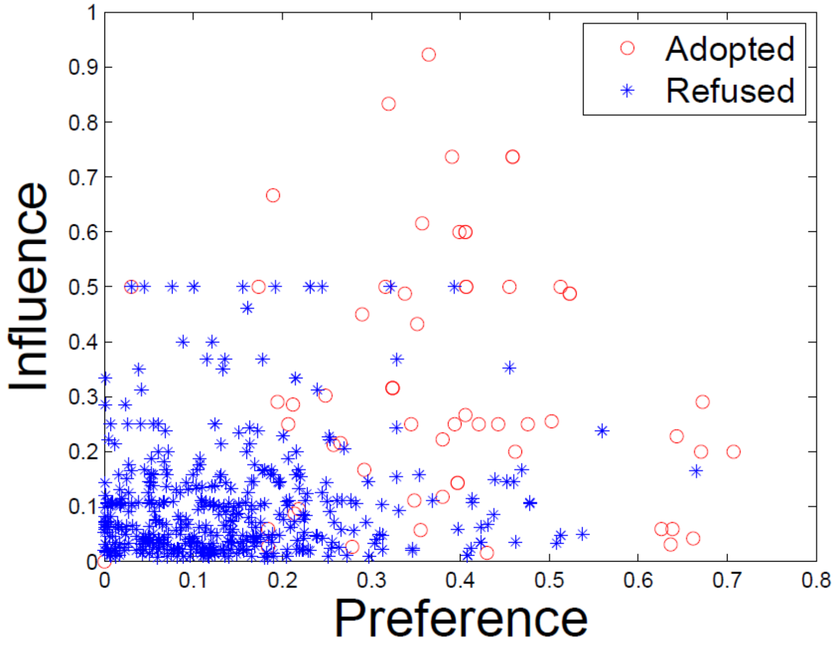
(3) adopt?

Observation: Social Contextual Factors

❖ Individual Preference & Interpersonal Influence



China's Facebook:
Renren



China's Twitter:
Tencent Weibo

Representation: From Information to Factors

Content:

item content

Behavior:

user-item interaction

Social:

social relation

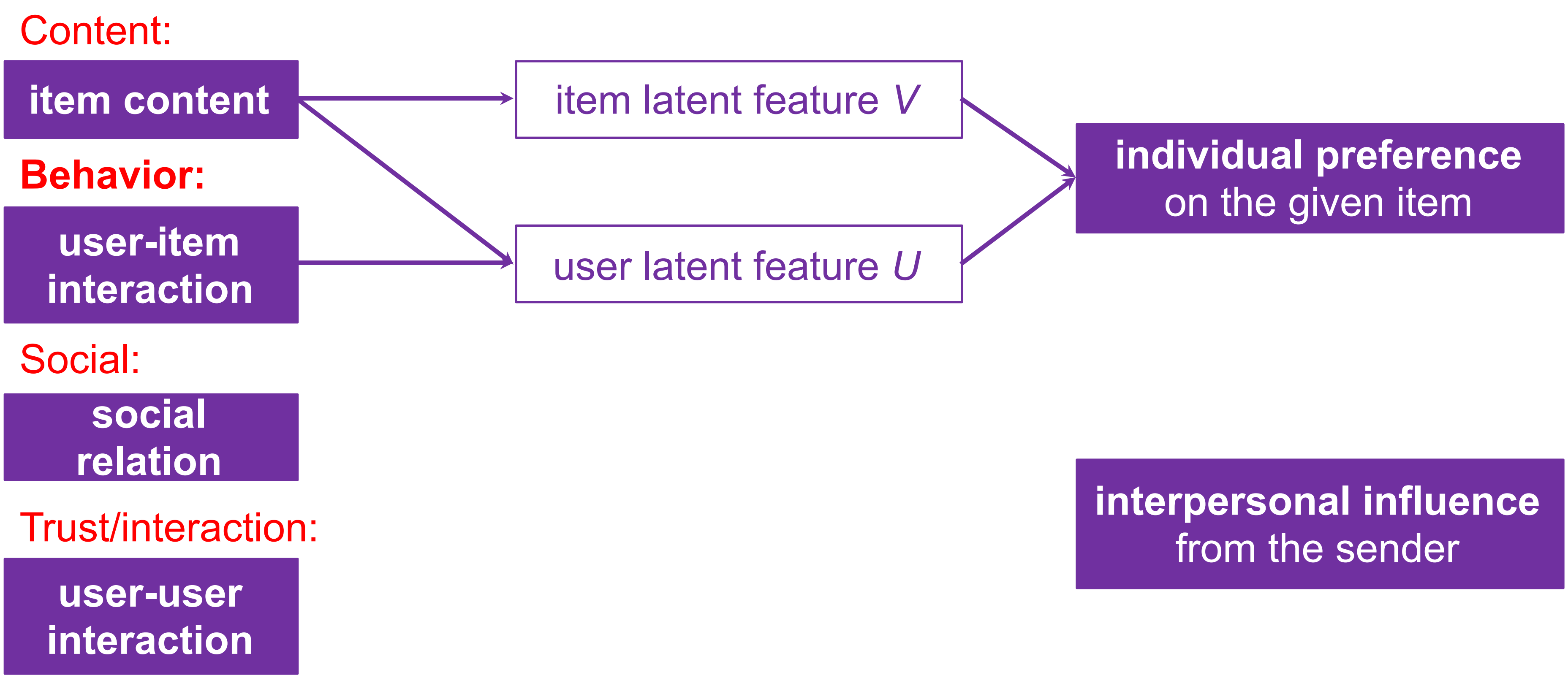
Trust/interaction:

user-user interaction

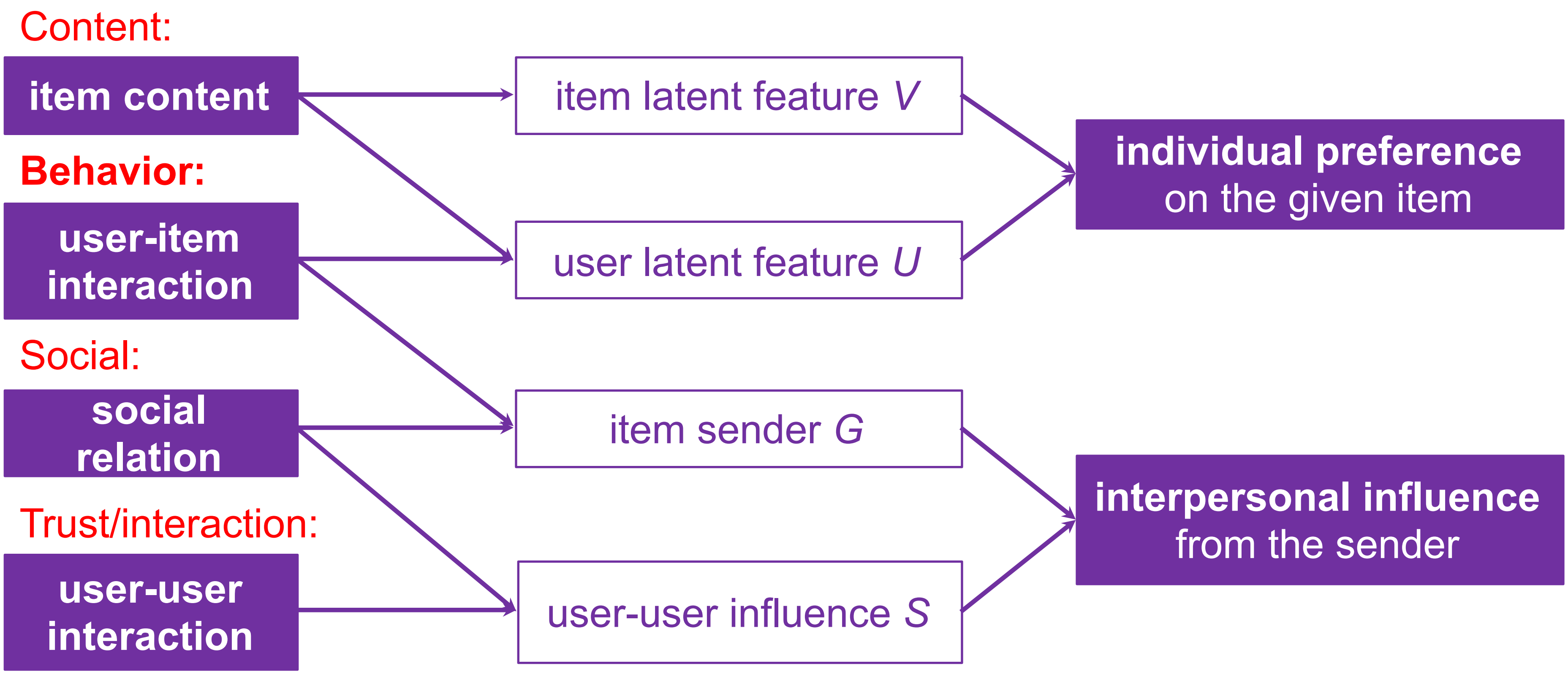
individual preference on the given item

interpersonal influence from the sender

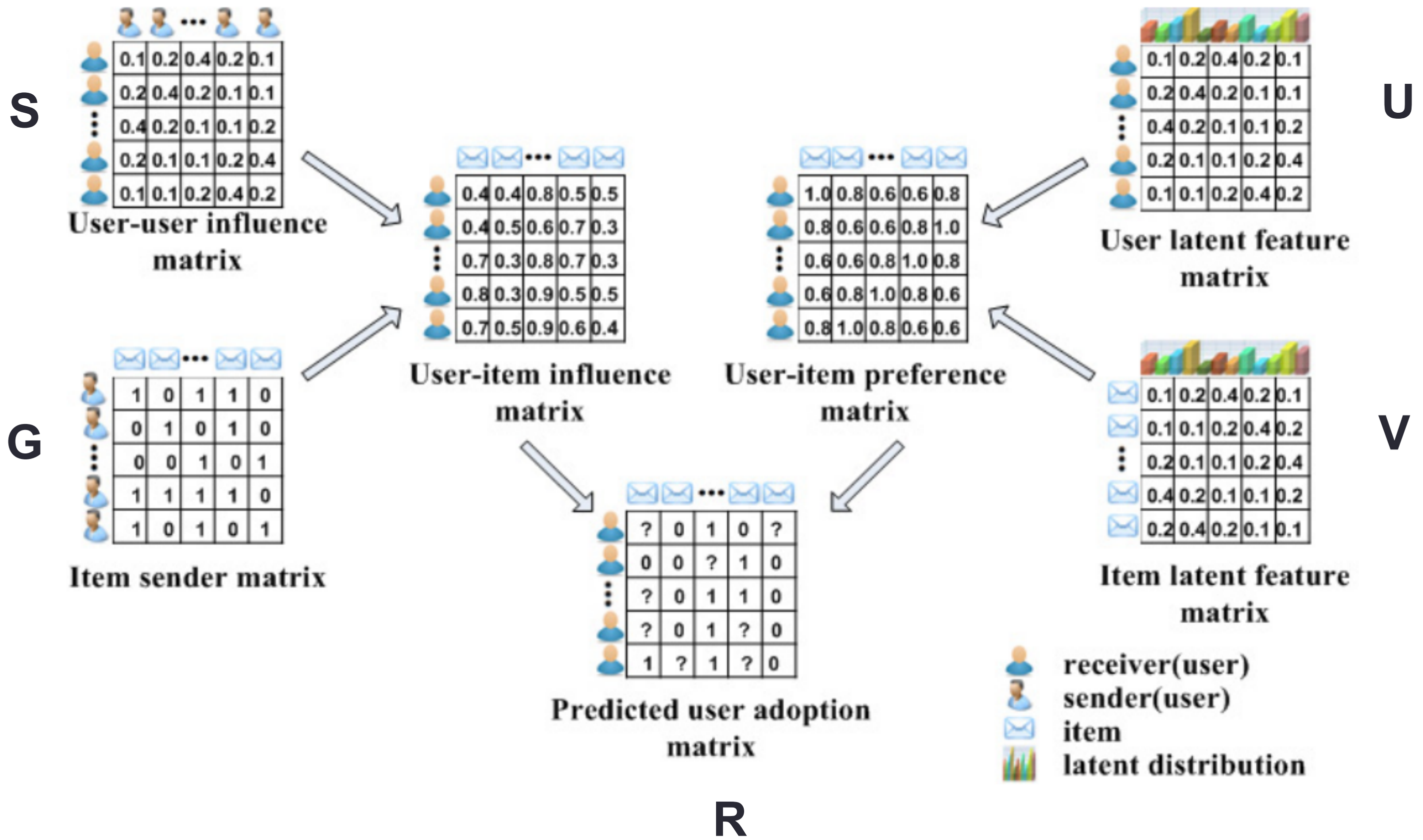
Representation: From Information to Factors



Representation: From Information to Factors



Algorithm: ContextMF
Social Contextual Recommendation



Algorithm: ContextMF
Social Contextual Recommendation

behavior influence preference

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

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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

Algorithm: ContextMF
Social Contextual Recommendation

Gradient Descent Methods

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

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

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

Results

	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**

Roadmap

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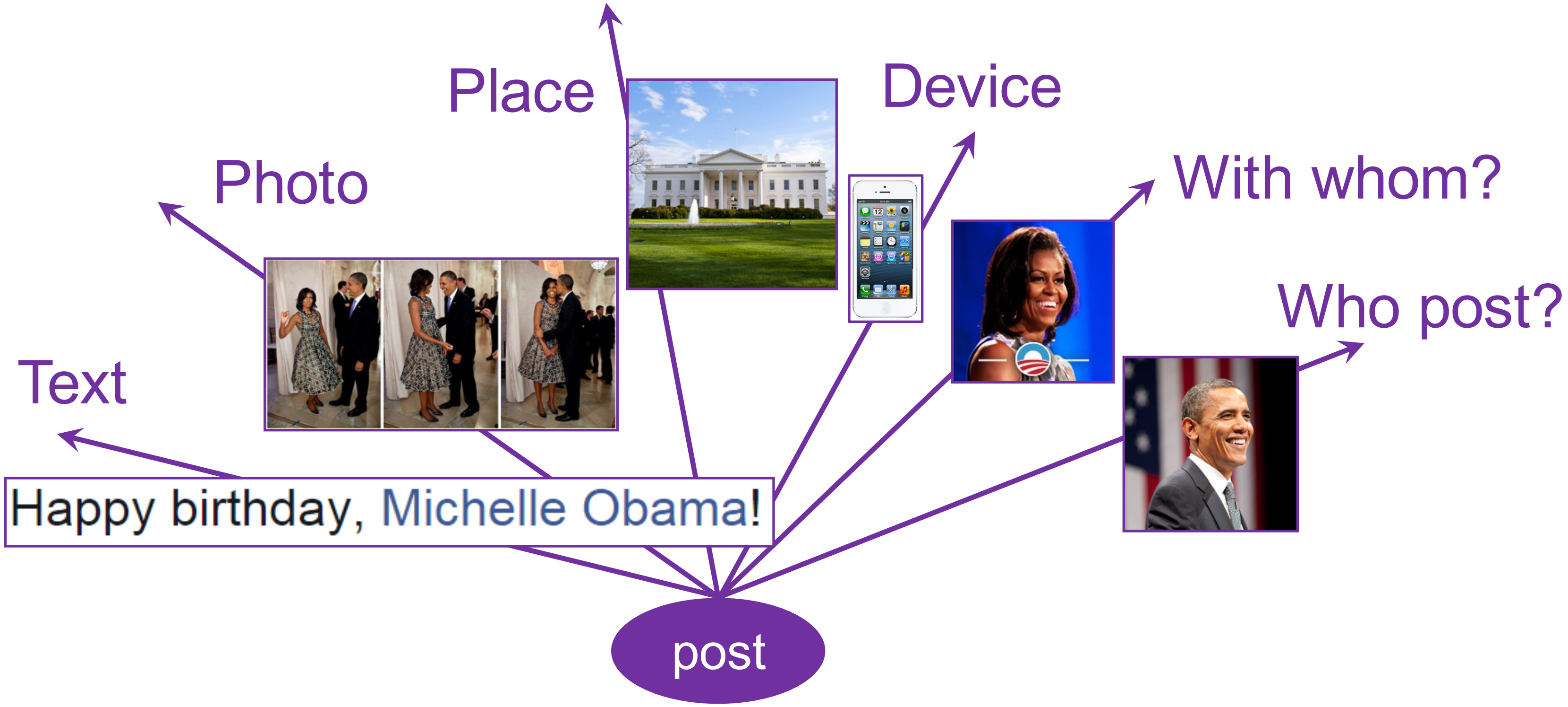
- Source
  - W3: Modeling cross-domain behaviors (CIKM'12, TKDE'15, 47 citations)
  - W4: Modeling cross-platform behaviors (AAAI'16)

Observation: Spatial Context



Jan. 18
Birthday party
@ White house

Observation: Temporal Context

Photo

Text

Happy birthday, Michelle Obama!

post

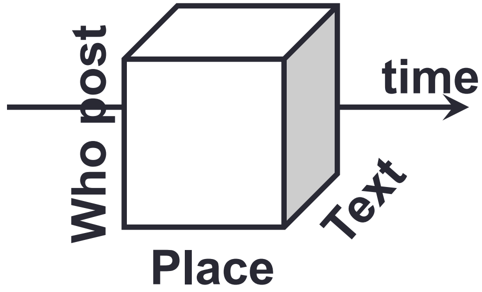
post

time

Jan. 18
Birthday party
@ White house

March 17
St. Patrick's Day
@ Bar

Representation: Tensor Sequence



Behavior

Spatial info: Multi-faceted

Temporal info: Dynamic

Tasks

Behavior modeling

Pattern discovery

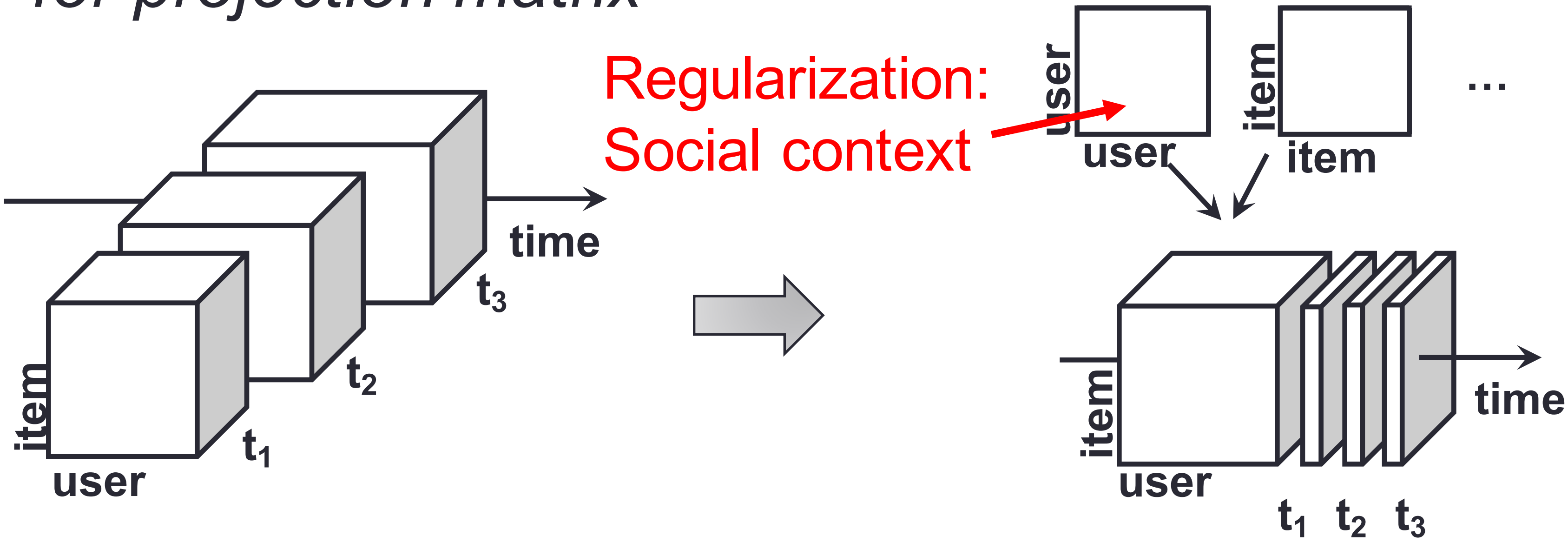
Behavior prediction

Tensor sequence

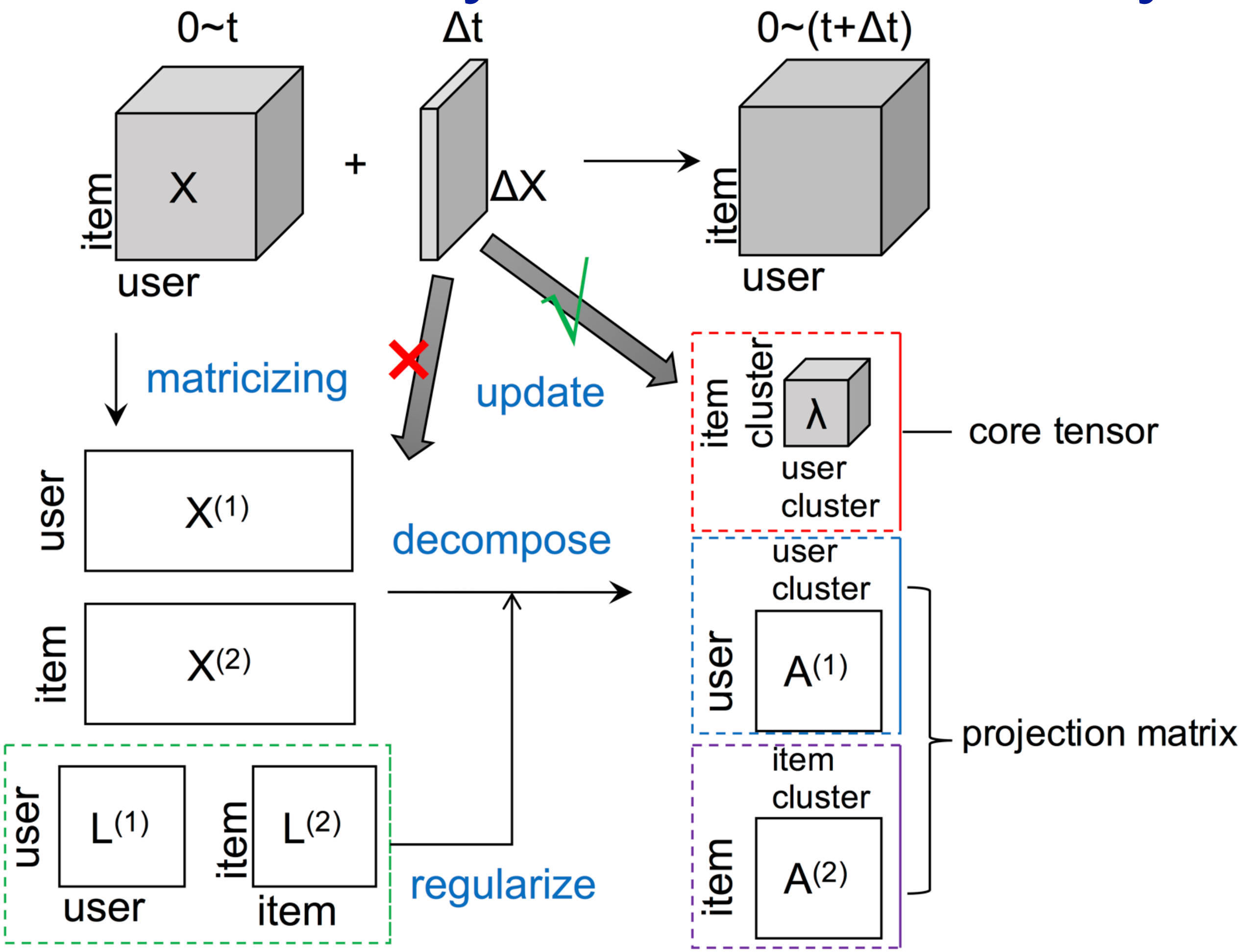
Decomposition & Completion

Challenges: Sparsity and Complexity

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

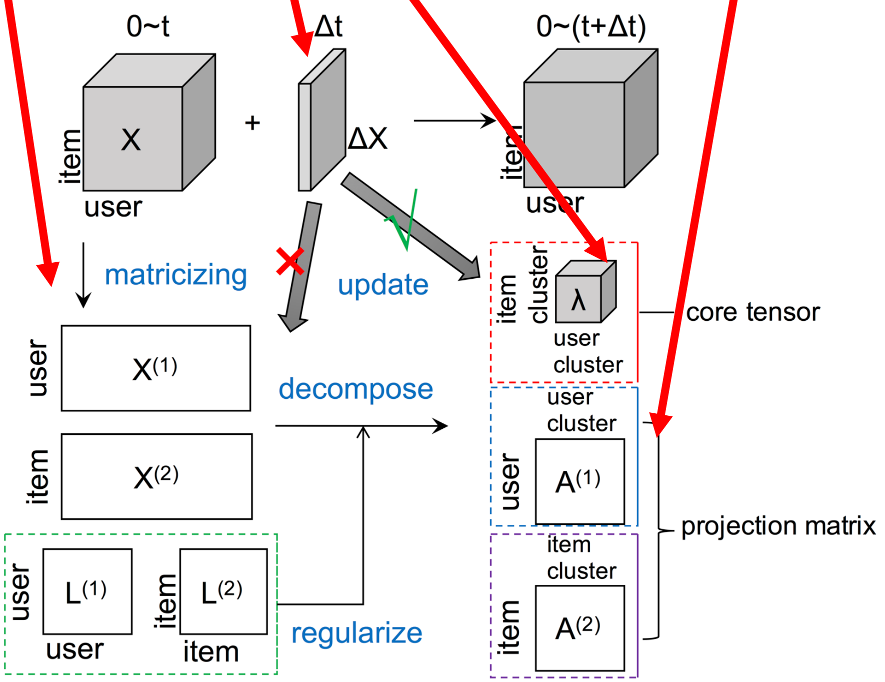


Algorithm: FEMA
Flexible Evolutionary Multi-faceted Analysis



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

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

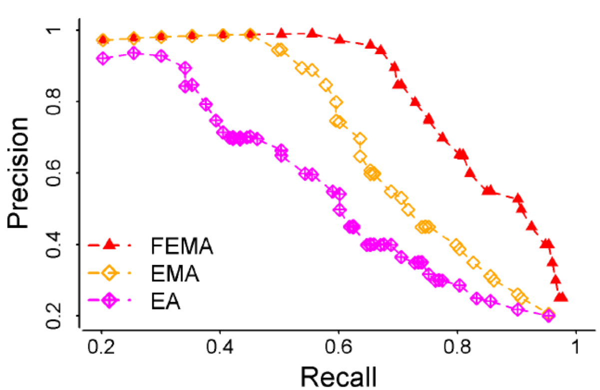
$$|\Delta\mathbf{a}_i^{(m)}| \leq 2\|\Delta\mathbf{X}^{(m)}\|_2\sum_{j\neq i}\frac{(\lambda^{\max}_{\mathbf{X}^{(m)\top}\mathbf{X}^{(m)}})^{\frac{1}{2}}}{|\lambda_i^{(m)} - \lambda_j^{(m)}|}$$

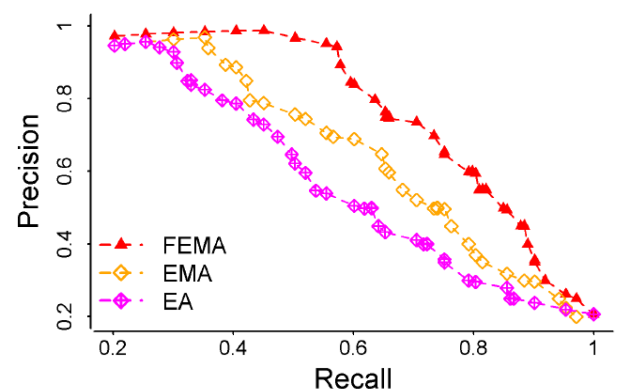
projection matrix

Results: FEMA > EMA > EA

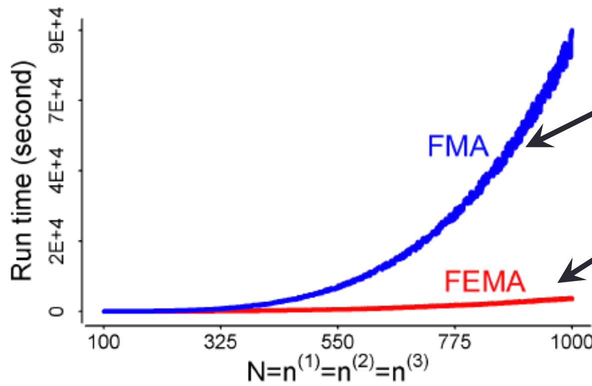
	Microsoft Academic Search		Tencent Weibo mentions “@”	
	MAE	RMSE	MAE	RMSE
FEMA X L	**0.735**	**0.944**	**0.894**	**1.312**
EMA X	0.794	1.130	0.932	1.556
EA X	0.979	1.364	1.120	1.873

Precision vs Recall





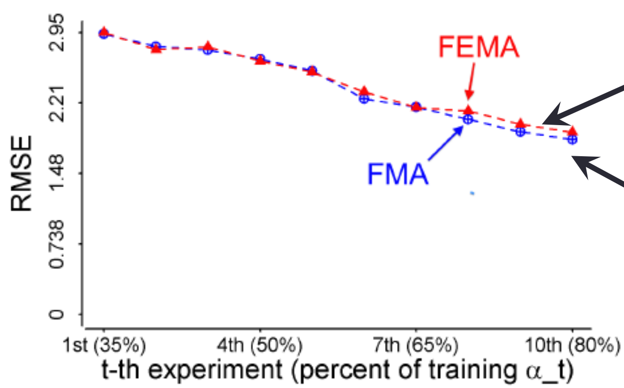
Results: Efficiency



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

Roadmap

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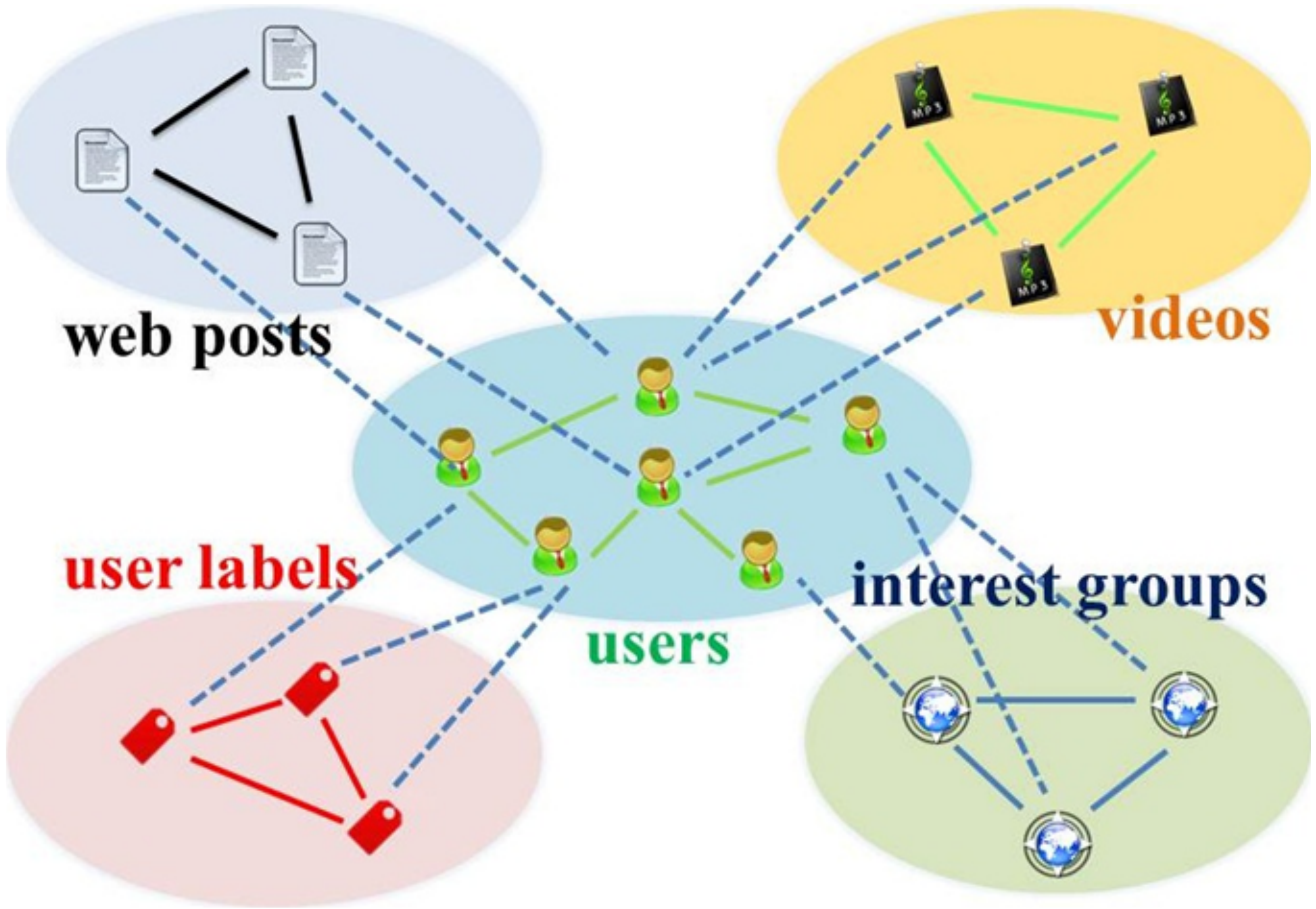
  - W4: Modeling cross-platform behaviors (AAAI’16)

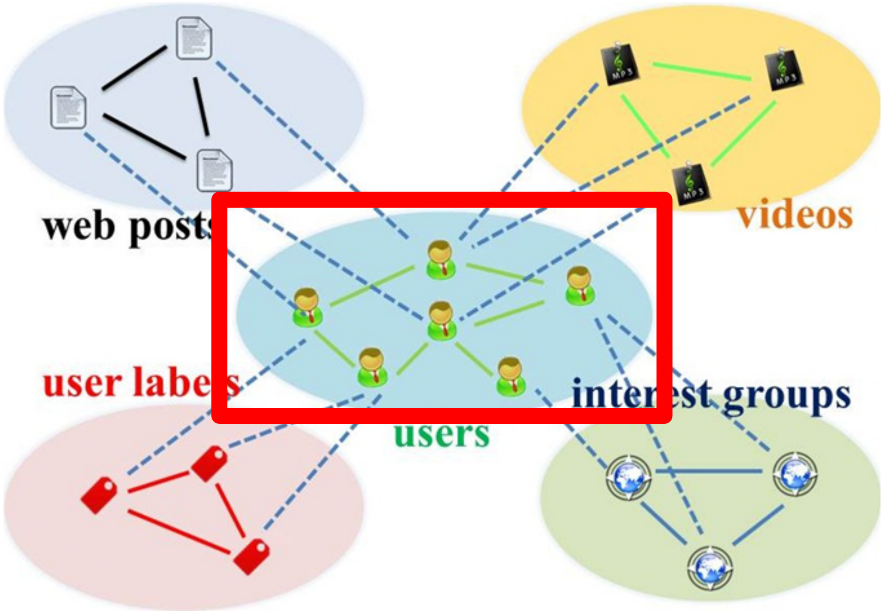
Observation: Multiple Domains

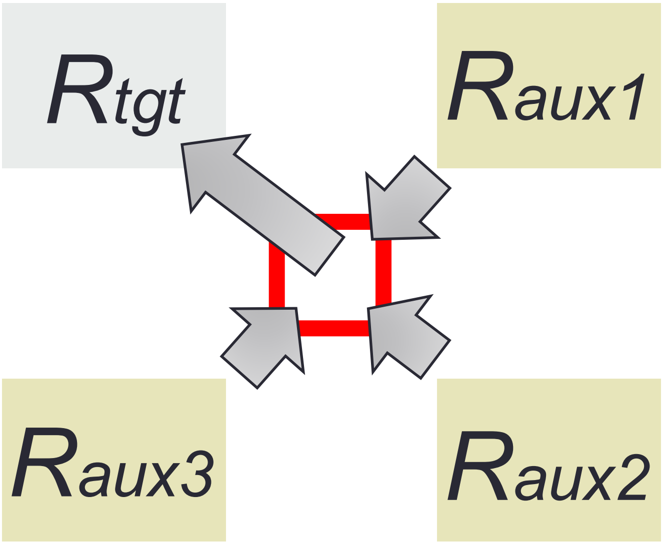
Religious Views	Christian
Interests	Basketball, writing, spending time w/ kids
Favorite Music	Miles Davis, John Coltrane, Bob Dylan, Stevie Wonder, Johann Sebastian Bach (cello suites), and The Fugees
Favorite Movies	Casablanca, Godfather I & II, Lawrence of Arabia and One Flew Over the Cuckoo's Nest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

Representation: Start-Structured Graph



Representation: Social Bridge

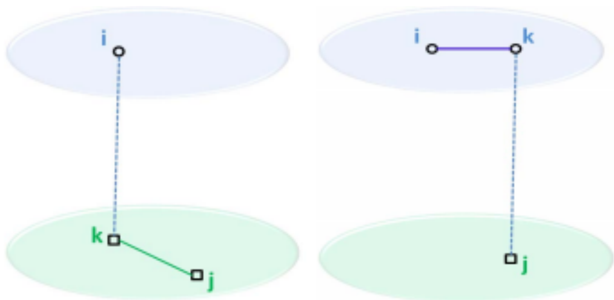




Bridge: Tie strength

Algorithm: Hybrid Random Walk

❖Updating cross-domain links



(a) Route 1 (b) Route 2

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

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

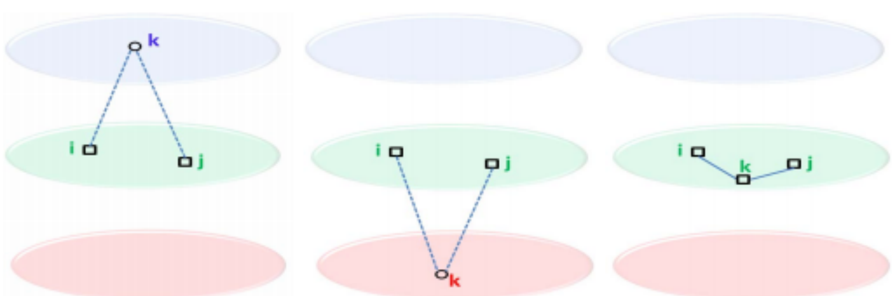
$$p_{ij}^{(\mathcal{UT})^+} = \eta \sum_{u_k \in \mathcal{U}} r_{ik}^{(\mathcal{U})} p_{kj}^{(\mathcal{UT})^+} + (1-\eta) \sum_{t_k \in \mathcal{T}} p_{ik}^{(\mathcal{UT})^+} r_{kj}^{(\mathcal{T})}$$

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

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

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

❖Updating within-domain links



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

$$r_{ij}^{(\mathcal{U})} = \tau^{(\mathcal{P})} \Big(\mu \sum_{p_k \in \mathcal{P}} p_{ik}^{(\mathcal{UP})^+} p_{jk}^{(\mathcal{UP})^+} + (1-\mu) \sum_{p_k \in \mathcal{P}} p_{ik}^{(\mathcal{UP})^-} p_{jk}^{(\mathcal{UP})^-}\Big)$$

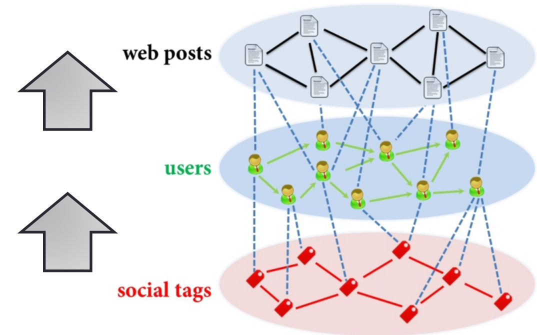
$$+ \tau^{(\mathcal{T})} \sum_{t_k \in \mathcal{T}} p_{ik}^{(\mathcal{UT})^+} p_{jk}^{(\mathcal{UT})^+} + \tau^{(\mathcal{U})} \sum_{u_k \in \mathcal{U}} r_{ik}^{(\mathcal{U})} r_{kj}^{(\mathcal{U})} \quad (12)$$

$$\mathbf{R}^{(\mathcal{U})}(t+1) =$$

$$\tau^{(\mathcal{P})} \Big(\mu \mathbf{P}^{(\mathcal{UP})^+}(t) \mathbf{P}^{(\mathcal{UP})^+}(t)^T + (1-\mu) \mathbf{P}^{(\mathcal{UP})^-}(t) \mathbf{P}^{(\mathcal{UP})^-}(t)^T\Big)$$

$$+ \tau^{(\mathcal{T})} \mathbf{P}^{(\mathcal{UT})^+}(t) \mathbf{P}^{(\mathcal{UT})^+}(t)^T + \tau^{(\mathcal{U})} \mathbf{R}^{(\mathcal{U})}(t) \mathbf{R}^{(\mathcal{U})}(t)^T \quad (13)$$

Results



Comparing with Random Walk with Restarts Models

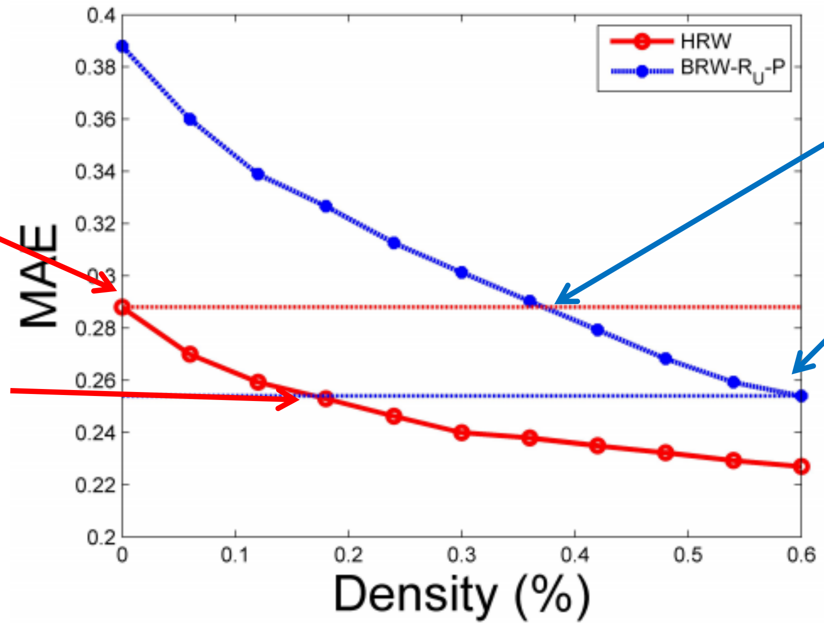
Algorithm	MAE	Precision	Recall	F1	Kendall's $\hat{\tau}$
HRW	**0.227±1.5e-3**	**0.711±1.3e-3**	0.921±1.4e-3	**0.802±1.1e-3**	**0.792±2.5e-3**
BRW-R_U-P (TrustWalker)	0.276±1.1e-3	0.657±7.6e-4	**0.935±9.8e-4**	0.772±7.6e-4	0.774±1.6e-3
BRW-R_U	0.282±5.3e-3	0.655±4.0e-3	0.921±1.2e-2	0.765±7.7e-3	0.725±2.8e-3
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



Roadmap

- Context
  - W1: Modeling social contexts (CIKM'12, TKDE'14, 129 citations) – online environment (mechanism)
  - W2: Modeling spatiotemporal contexts (KDD'14, 10 citations) – physical environment
- Source
  - W3: Modeling cross-domain behaviors (CIKM'12, TKDE'15, 47 citations)
  - **W4: Modeling cross-platform behaviors (AAAI'16)**

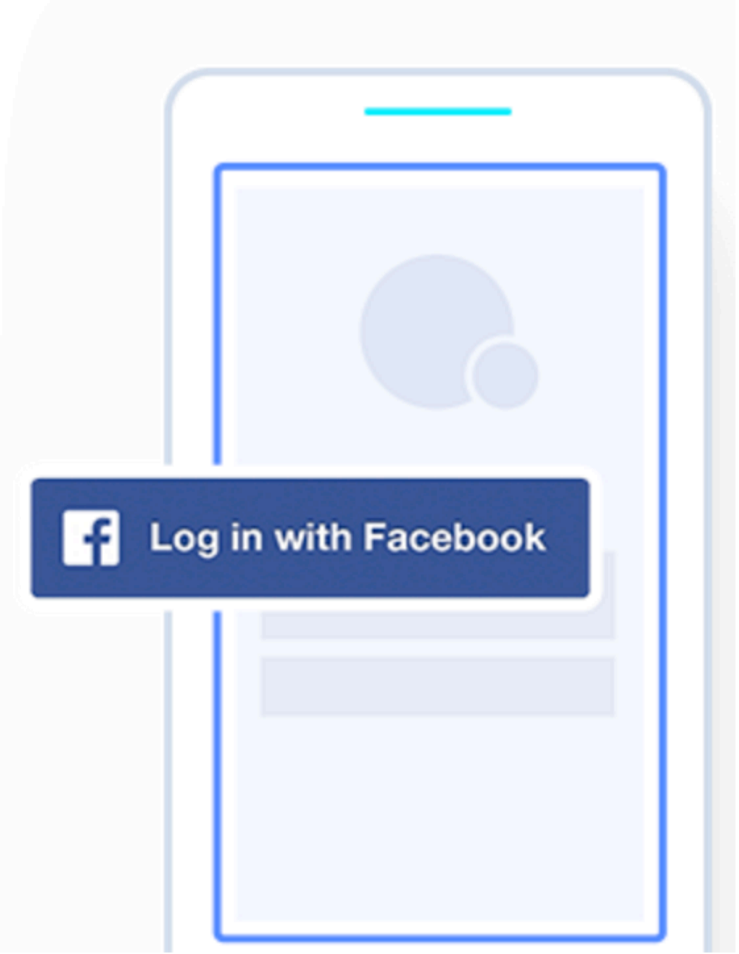
Observation: Multiple Platforms

Observation: Cross-Platform

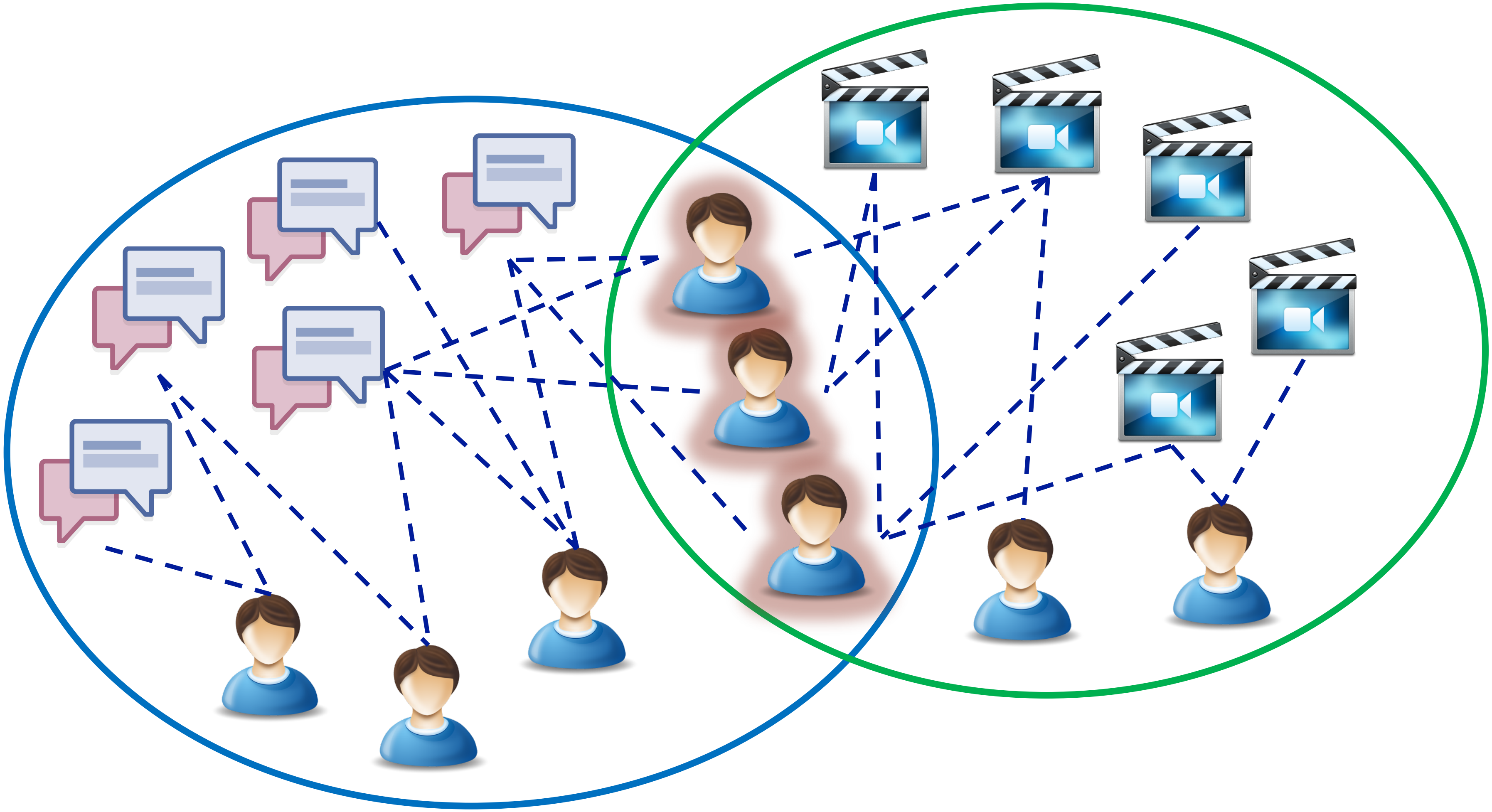
Add Facebook Login to Your App or Website

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

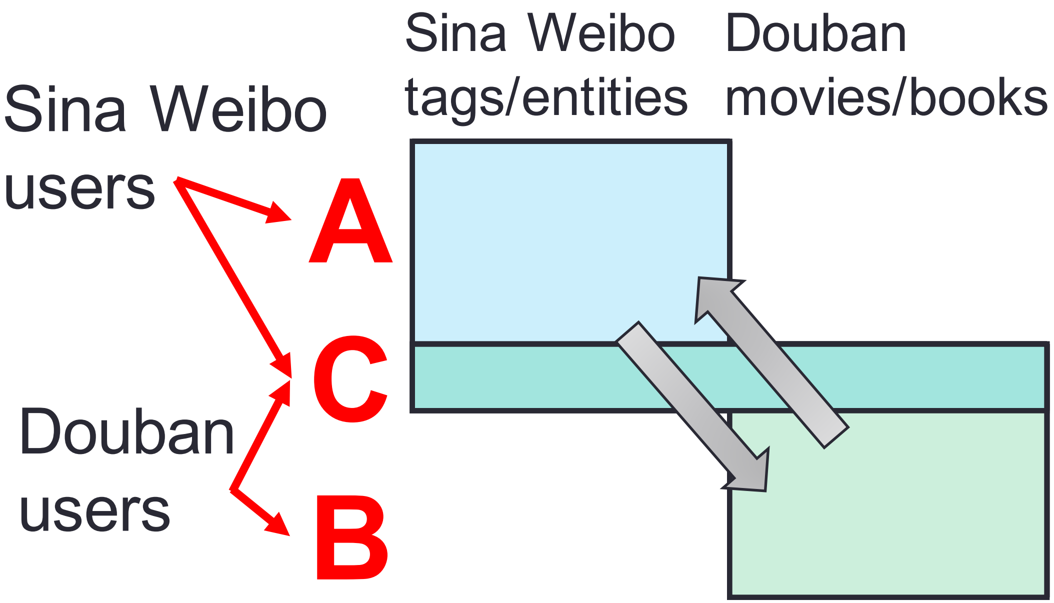
- iOS
- Android
- Websites or mobile websites
- More platforms

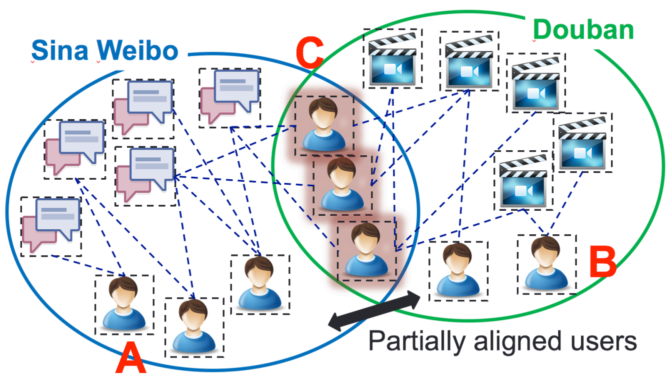


Observation: Partially Overlapped Crowds



Representation: When NO Transfer

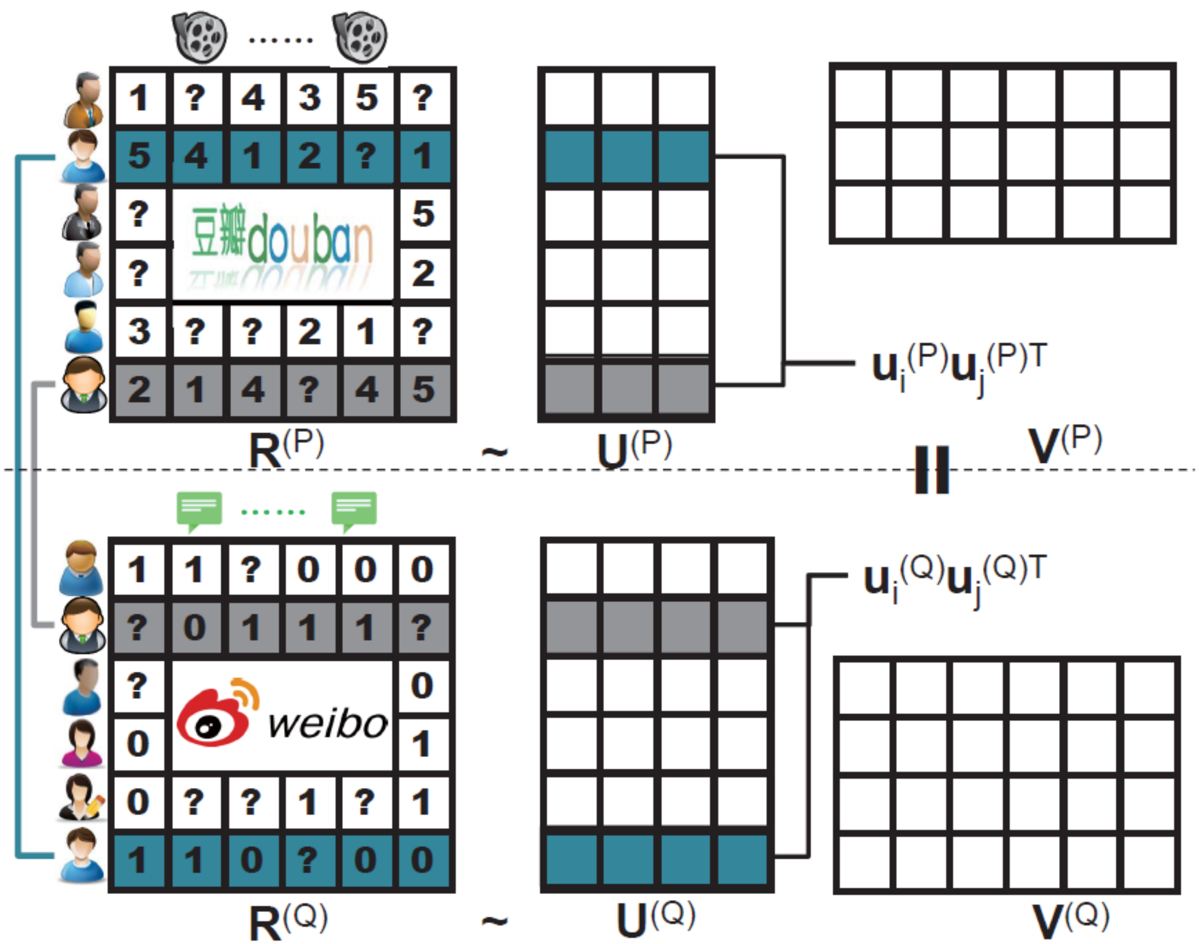




User set	Weibo tweet entity to Douban movie	
	RMSE	MAP
A	Auxiliary platform data!	
C	**0.779**	**0.805**
B	1.439	0.640

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**

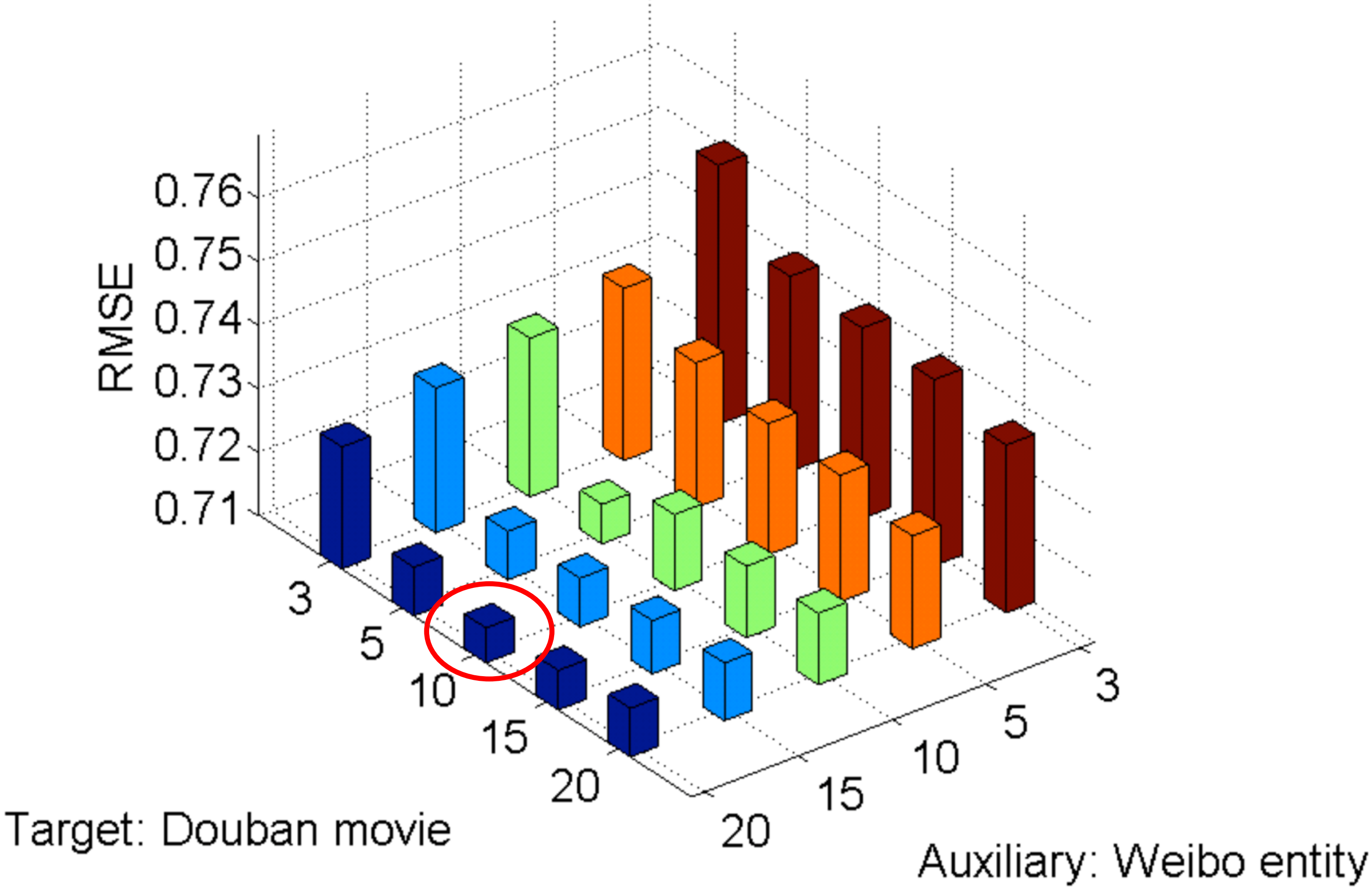
User set	Douban book to Weibo social tag	
	RMSE	MAP
A	**0.429**	**0.464**
C	0.267	0.666
B	Auxiliary platform data!	

Transfer via Different Latent Spaces

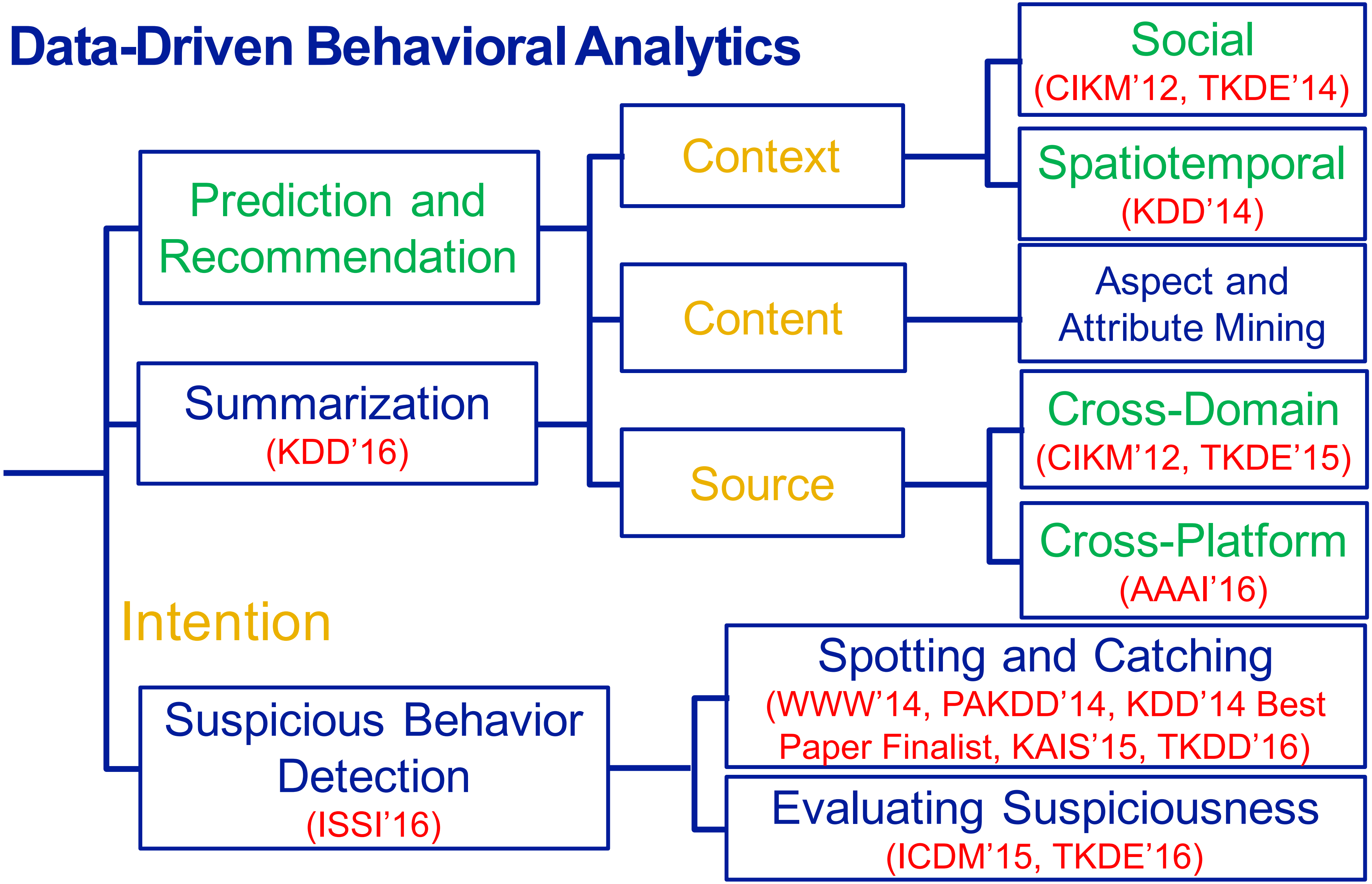
User set	Weibo tweet entity to Douban movie	
	RMSE	MAP
A		
C	0.715	0.821
B	**0.722**	**0.820**

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



Data-Driven Behavioral Analytics



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[1] Meng Jiang, Peng Cui, Rui Liu, Qiang Yang, Fei Wang, Wenwu Zhu, Shiqiang Yang. “Social Contextual Recommendation”, ACM CIKM 2012.

[2] Meng Jiang, Peng Cui, Fei Wang, Wenwu Zhu, Shiqiang Yang. “Scalable Recommendation with Social Contextual Information”, IEEE TKDE 2014. (IF=2.07)

[3] Meng Jiang, Peng Cui, Fei Wang, Xinran Xu, Wenwu Zhu, Shiqiang Yang. “FEMA: Flexible Evolutionary Multi-Faceted Analysis for Dynamic Behavioral Pattern Discovery”, ACM SIGKDD 2014. (Oral, ACC=14.6%)

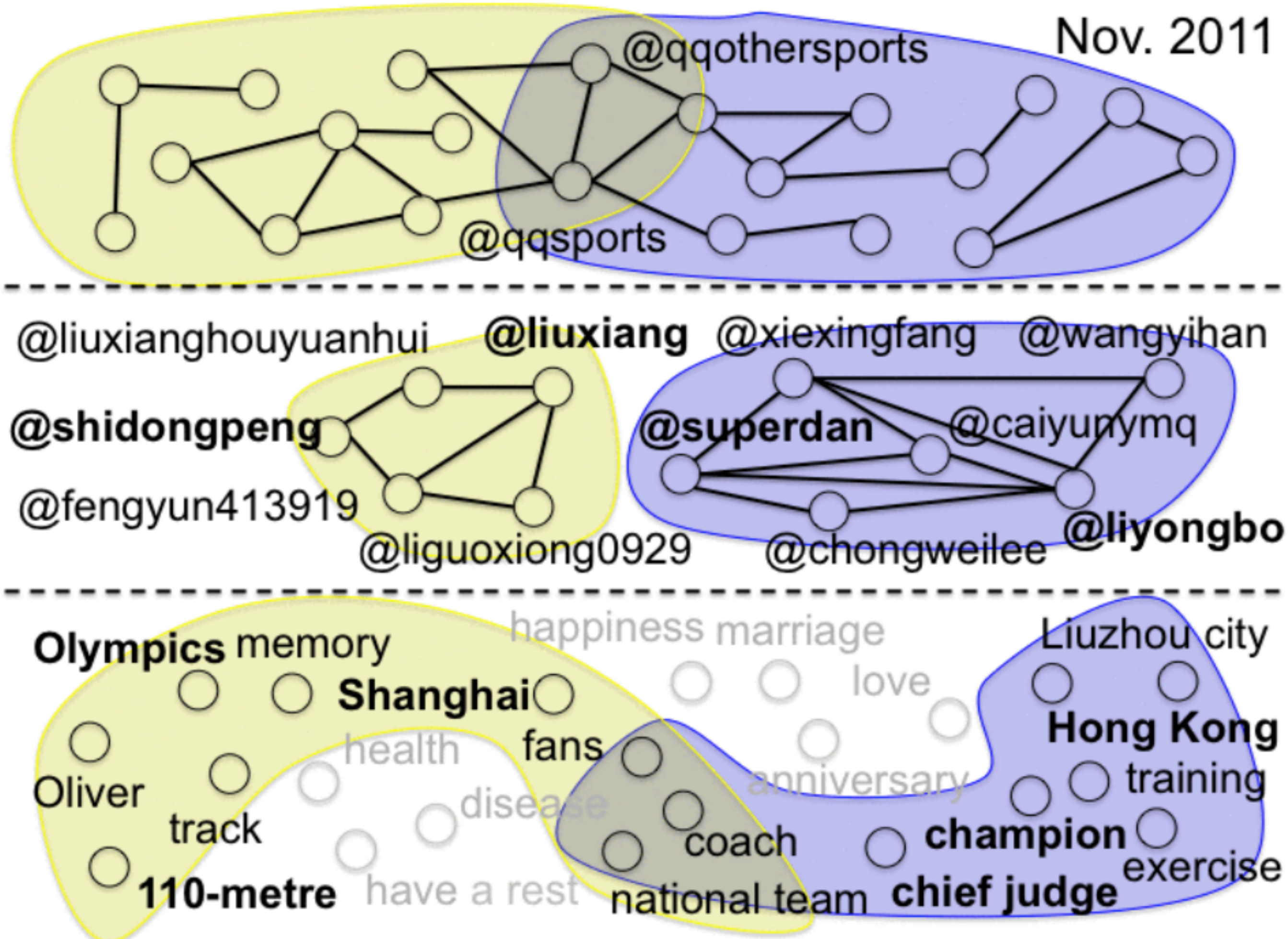
[4] Meng Jiang, Peng Cui, Fei Wang, Qiang Yang, Wenwu Zhu, Shiqiang Yang. “Social Recommendation across Multiple Relational Domains”, ACM CIKM 2012.

[5] Meng Jiang, Peng Cui, Xumin Chen, Fei Wang, Wenwu Zhu, Shiqiang Yang. “Social Recommendation with Cross-Domain Transferable Knowledge”, IEEE TKDE 2015. (IF=2.07)

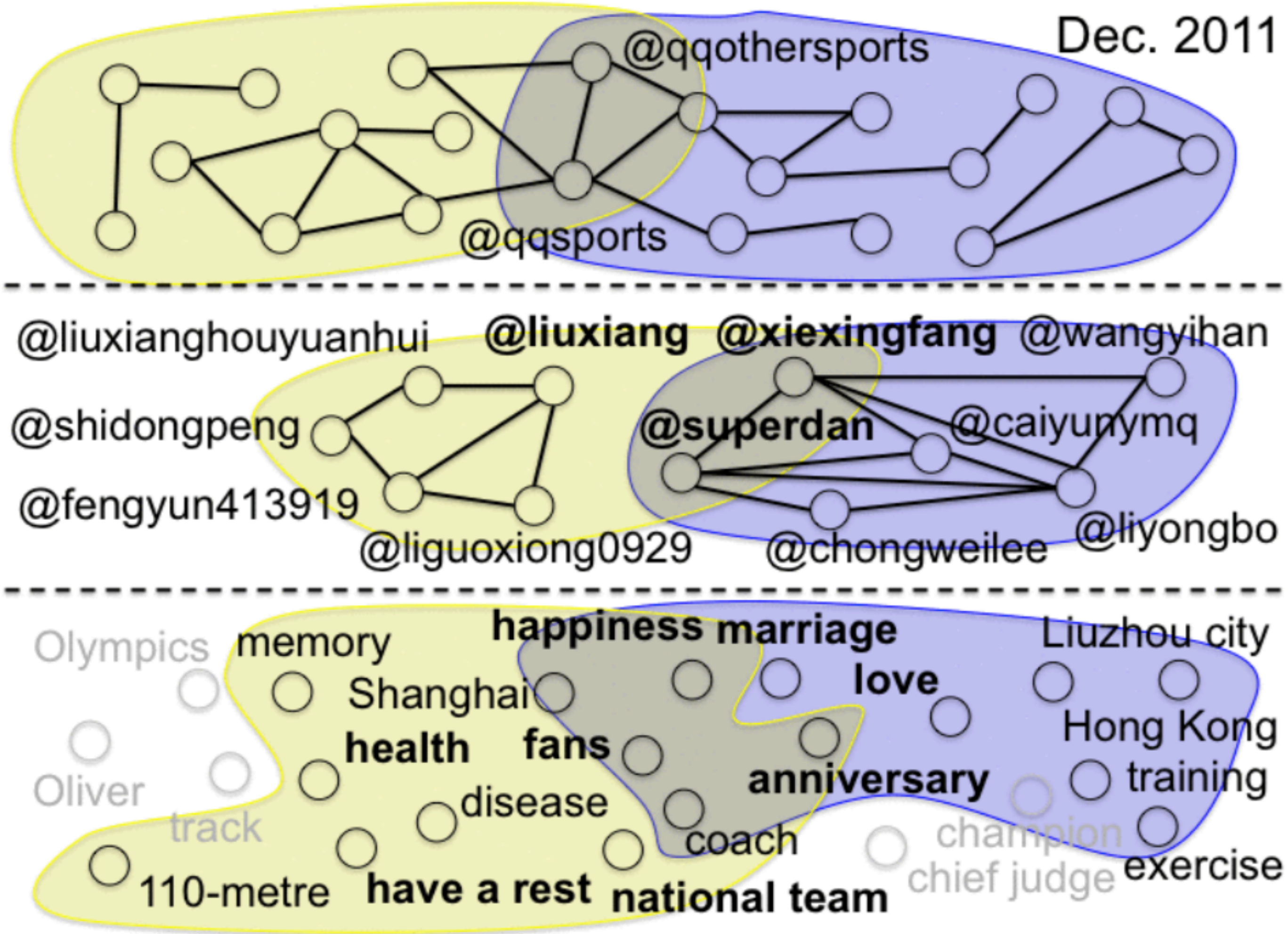
[6] Meng Jiang, Peng Cui, Nicholas Jing Yuan, Xing Xie, Shiqiang Yang. “Little is Much: Bridging Cross-Platform Behaviors through Overlapped Crowds”, AAAI 2016.

THANK YOU!

Results (FEMA)

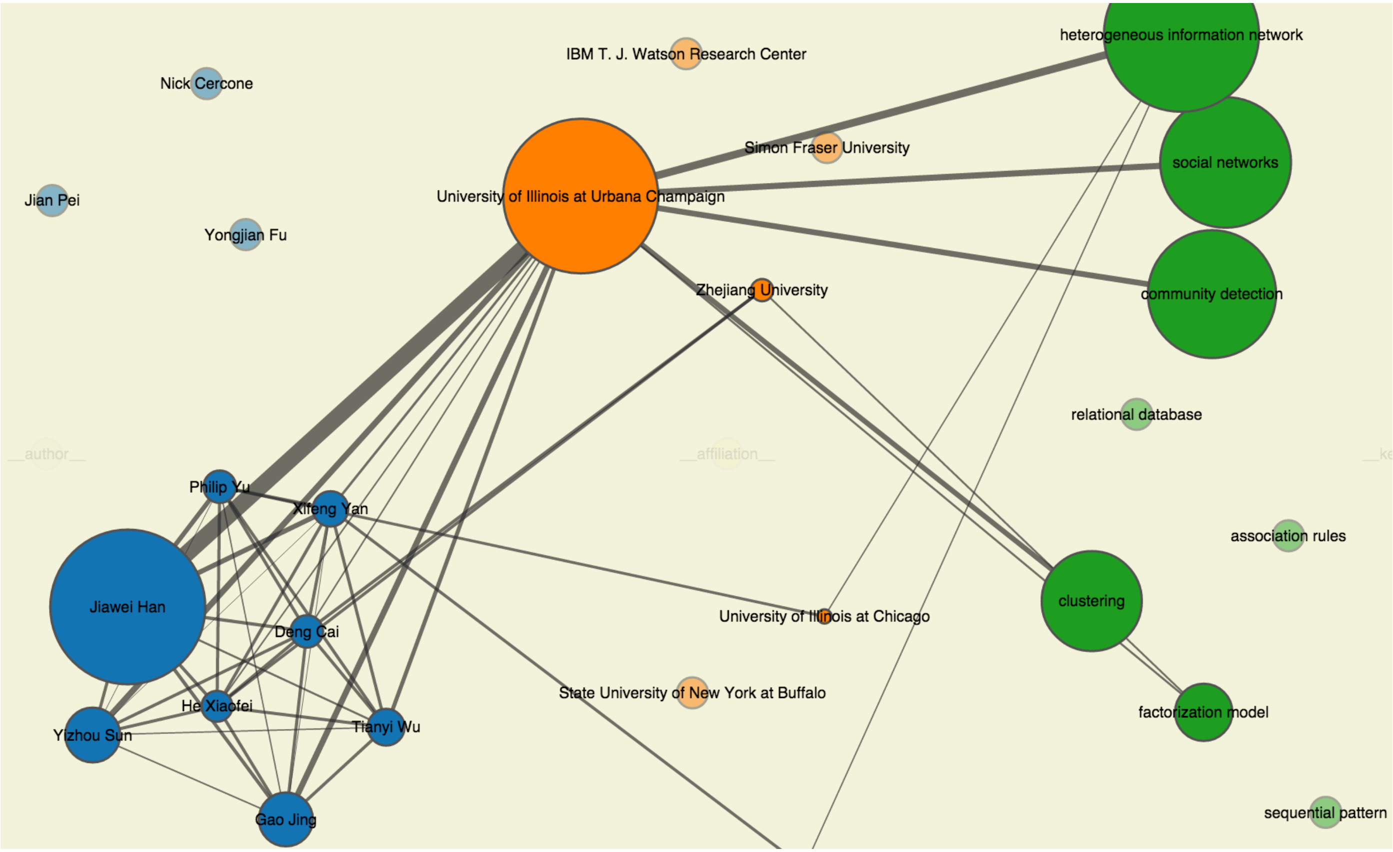


Results (FEMA)



Results (FEMA)

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



Results (XPTrans)