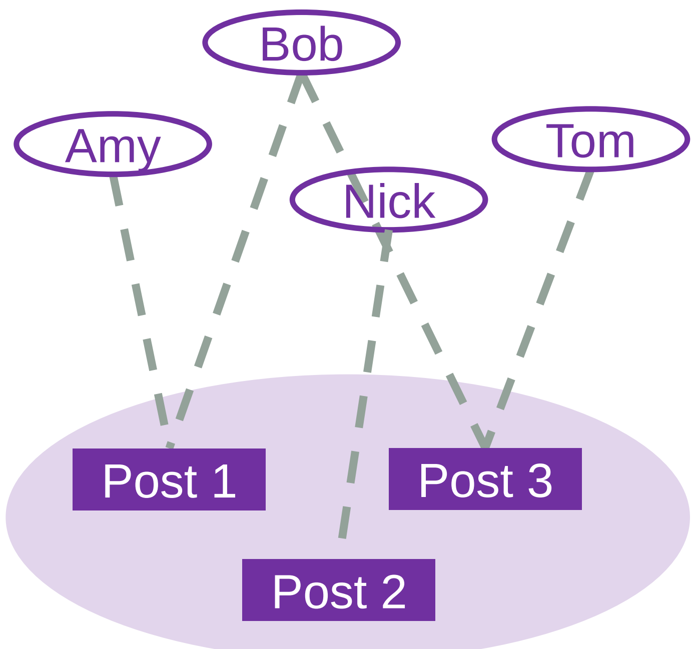
SOCIAL CONTEXTUAL RECOMMENDATION

Meng Jiang

Joint work with Peng Cui, Rui Liu, Qiang Yang,
Fei Wang, Wenwu Zhu and Shiqiang Yang
October 30, 2012 – Maui, HI, USA

Recommender Systems

Predict missing “user-item” links → Predict missing values in “user-item” matrix → Challenge: High sparsity



	Amy	Bob	…	User M
Post 1	1	1	…	0
Post 2	?	0	…	?
…	…	…	…	
Post N	0	?	…	1

Our Goals

- Given: Links on social networks
- Find: A social recommendation framework that best fit users' adopting behaviors

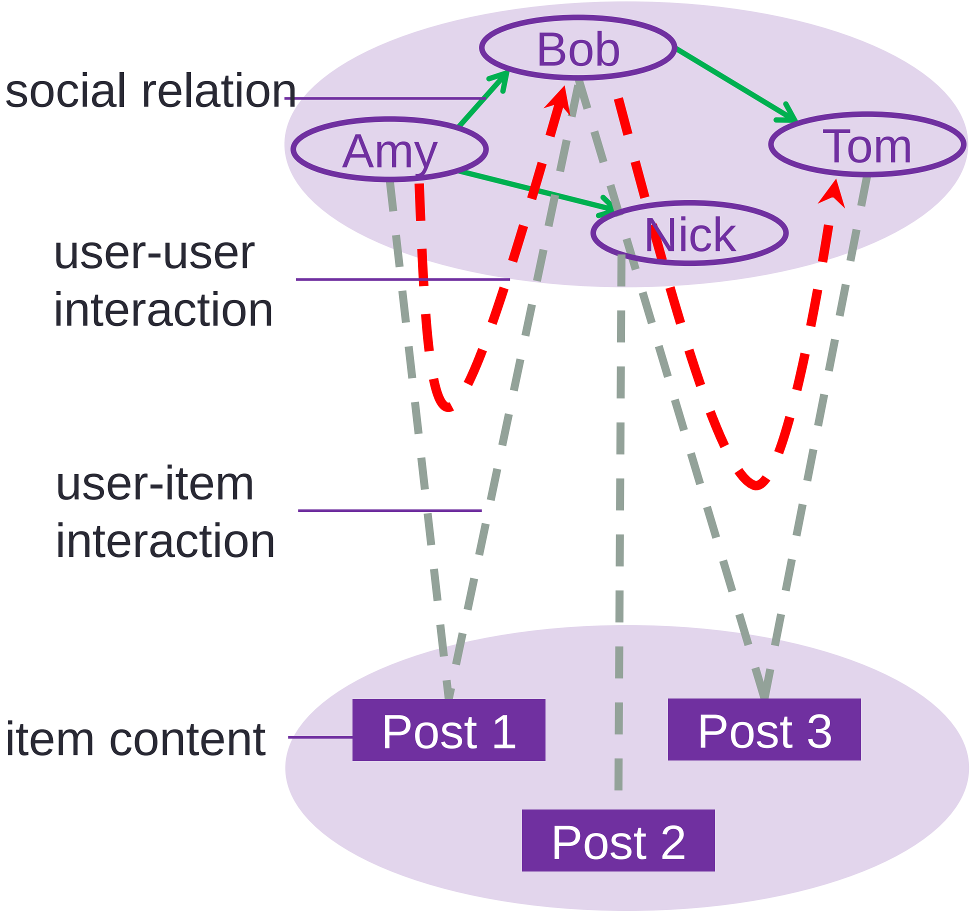
- Goals:
  - G1. Understand user intention of adoption
  - G2. A framework for social recommendation
  - G3. Predict the missing "user-item" links

OUTLINE

Links on Social Networks

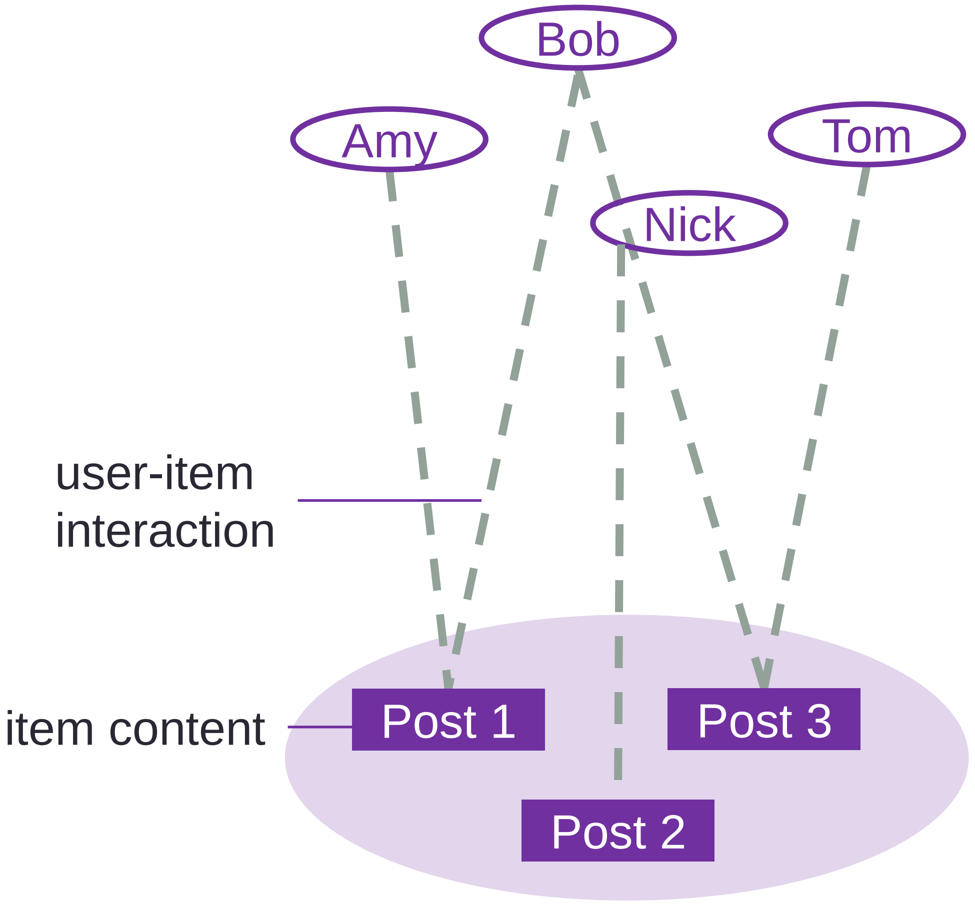
- Target: “user-item” links
- Nature: “user-user” links

- Can social relation help?
- How to use social contextual information?



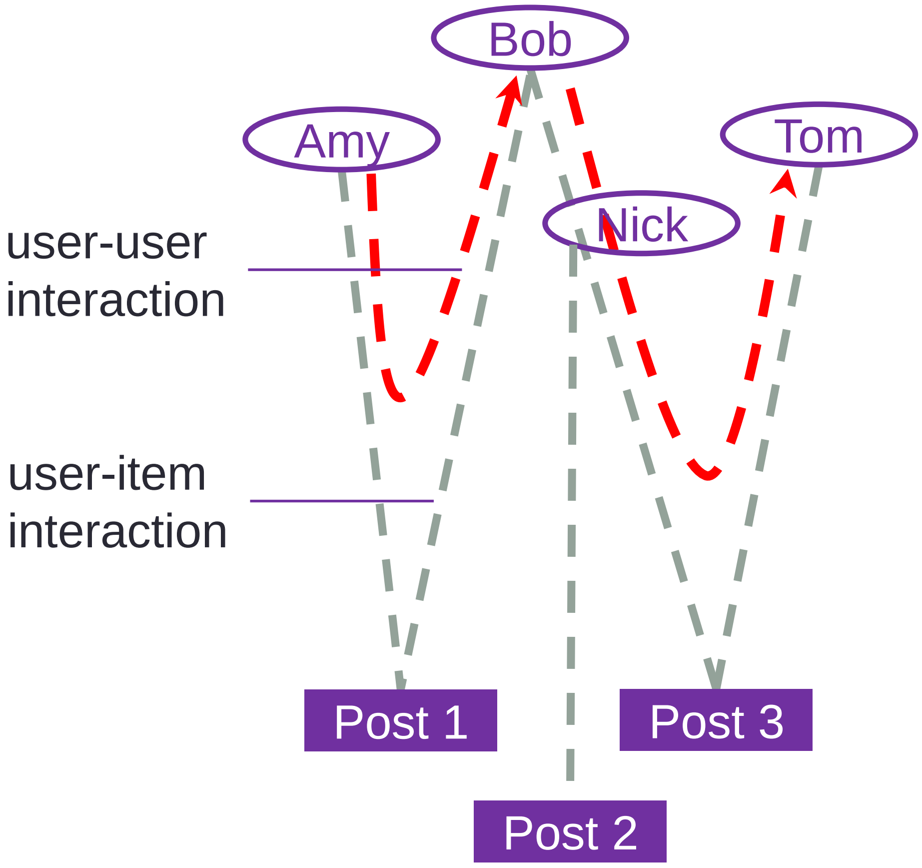
Related Works

- Content-based filtering
- Collaborative filtering



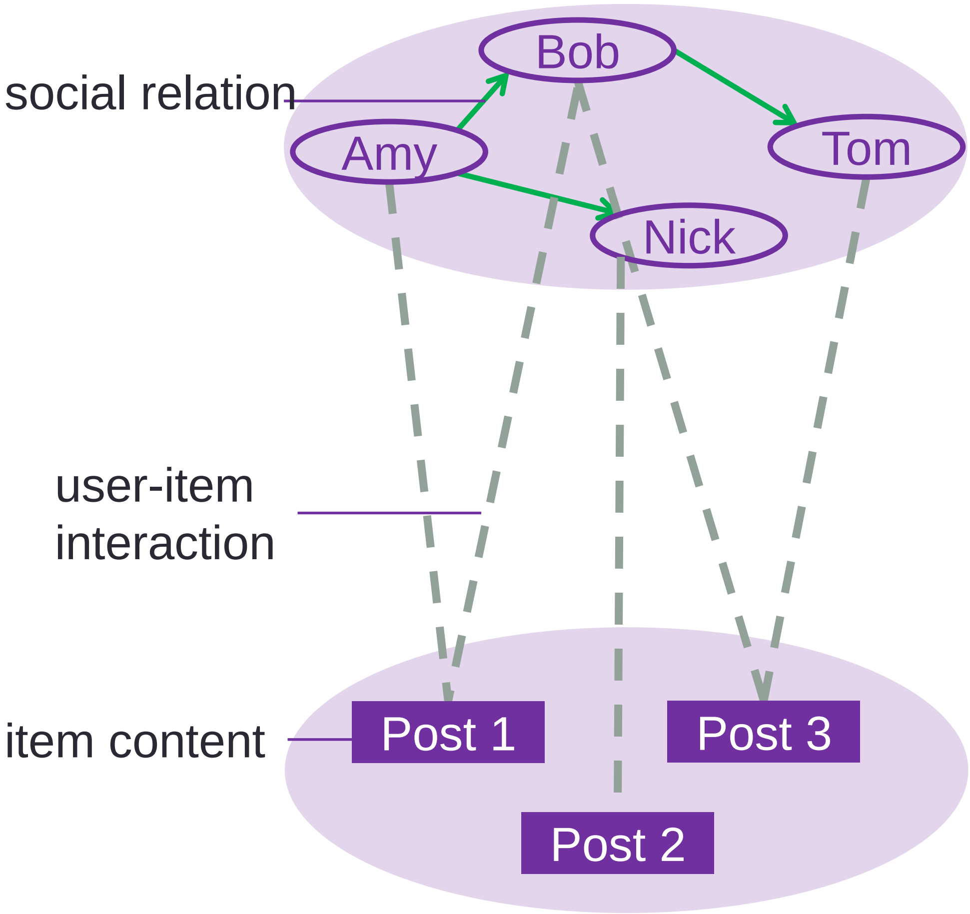
Related Works

- Content-based filtering
- Collaborative filtering
- Trust-based recommendation
- Influenced-based recommendation



Related Works

- Content-based filtering
- Collaborative filtering
- Trust-based recommendation
- Influenced-based recommendation
- Social recommendation with MF/Social Regularization



Related Works

	Social relation	User-user interaction	User-item interaction	Item content
Content-based & CF	×	×	√	√
Trust & Influence	×	√	√	×
SoRec & SoReg	√	×	√	√
?	√	√	√	√

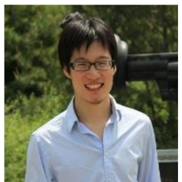
- Can we fully use social contextual information?

- Q: “Large-scale”? A: “Relational”!
- Q: “Relational”? A: “**Intention**”!

OUTLINE

1. Background
2. **Understanding Intention**
3. The Framework
4. ContextMF Algorithm
5. Experiments

User Intention of Adopting Messages



Peng Cui : Is there anyone who call for paper via Renren? Hah! http://media.cs.tsinghua.edu.cn/~multimedia/cuipeng/IR_SI_SocialMedia.htm

2011-01-05 13:47 Reply | Share

Call for paper? About social media? Wow! **Personal Preference**

This is my best friend and co-author! **Interpersonal influence**

Meng Jiang : Support! //Peng Cui : Is there anyone who call for paper via Renren? Hah! http://media.cs.tsinghua.edu.cn/~multimedia/cuipeng/IR_SI_SocialMedia.htm

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User Intention of Adopting Messages

Maosong Sun : KDD Summer School on Mining the Big Data will be held in Tsinghua. This is the first time for KDD to hold Summer School. Dean Xiaoyong Du, Dr. Hang Li and me are the Chairs. Today Jiawei Han(UIUC), Christos Faloutsos(CMU) and Bing Liu(UIC) gave lectures for 2 hours each.

2012-08-10 21:47 Retweet | Save | Reply

Amazing! Summer school! It is KDD!
Jiawei Han! Christos Faloutsos! Bin Liu!

Personal Preference

Interpersonal influence

This is the Dean of my Department!
His research area is Artificial Intelligence and Data Mining!

Meng Jiang : Amazing! //Maosong Sun : KDD Summer School on Mining the Big Data will be held in Tsinghua. This is the first time for KDD to hold Summer School. Dean Xiaoyong Du, Dr. Hang Li and me are the Chairs. Today Jiawei Han(UIUC), Christos Faloutsos(CMU) and Bing Liu(UIC) gave lectures for 2 hours each.

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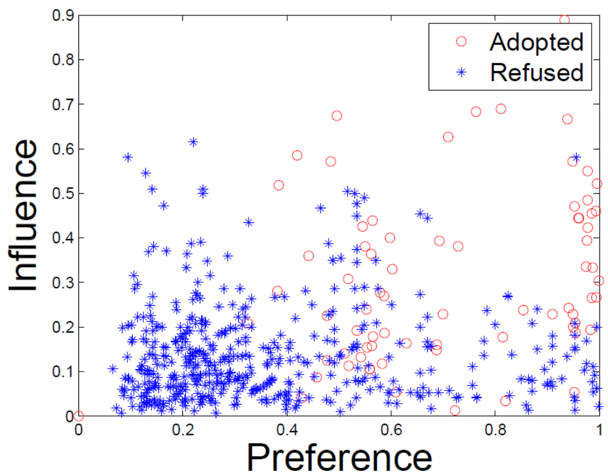
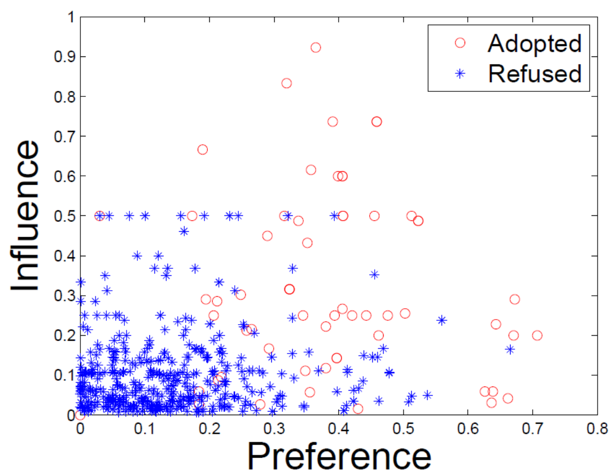
User Intention of Adopting Messages

- What is the item content? Who is the sender?

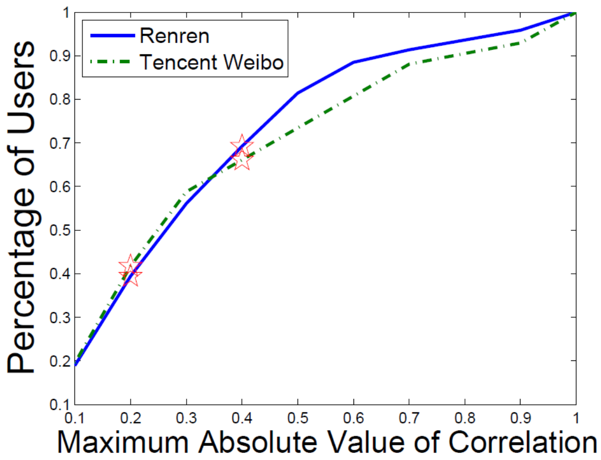
- Preference: topic-level user-item similarity
- Influence: user-sender interaction frequency



Renren



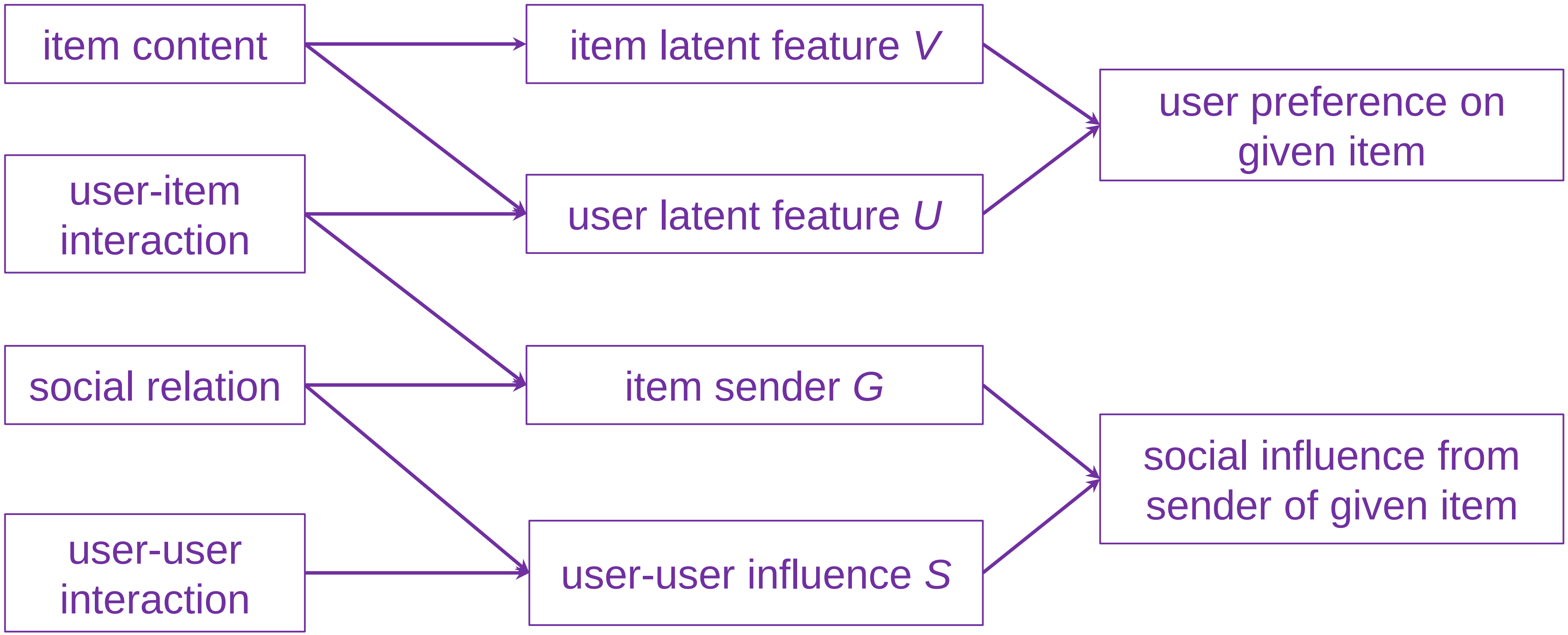
Tencent Weibo



Correlation(Preference, Influence) is small.

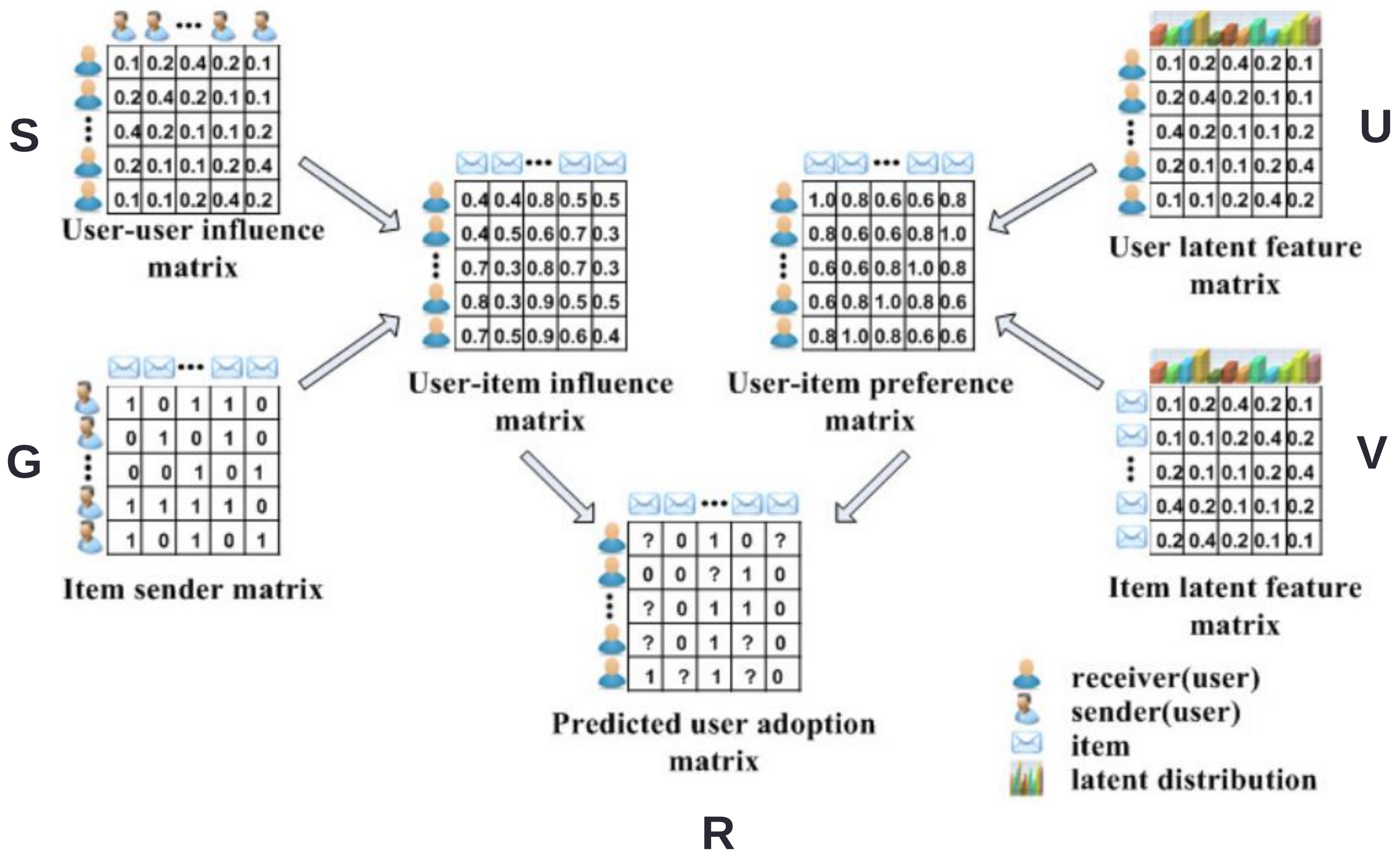
OUTLINE

Social Contextual Information/Factors



Social Contextual Recommendation

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



OUTLINE

ContextMF Algorithm

- Minimize sum-of-squared errors function

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

- Block coordinate descent scheme with gradients.

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

OUTLINE

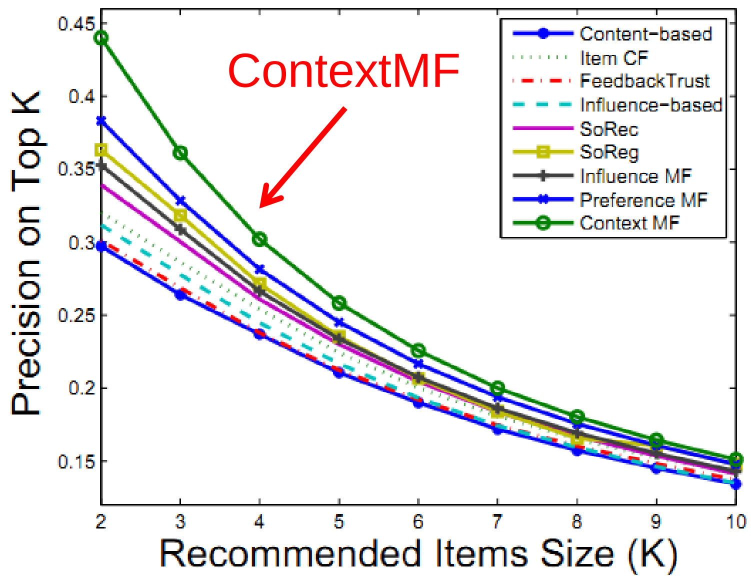
1. Background
2. Understanding Intention
3. The Framework
4. ContextMF Algorithm
5. **Experiments**

Effectiveness in Predicting Missing Links

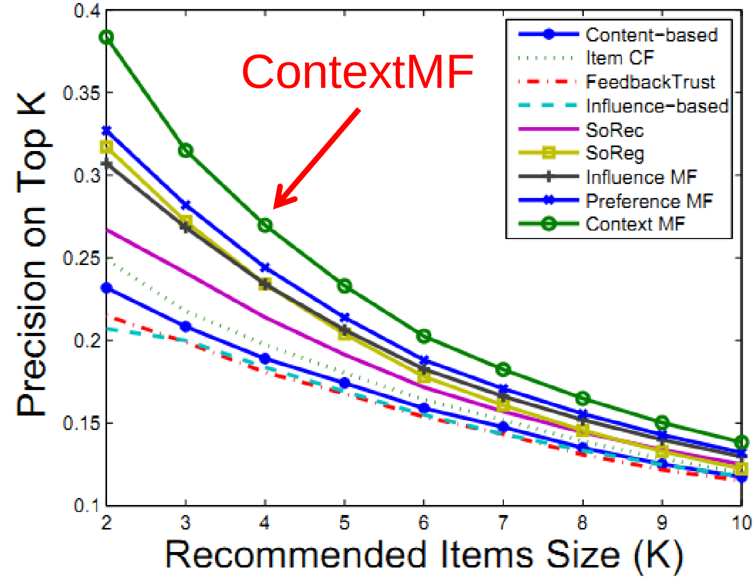
Method	MAE	RMSE	$\hat{\tau}$	$\hat{\rho}$
Renren Dataset				
Content-based [1]	0.3842	0.4769	0.5409	0.5404
Item CF [25]	0.3601	0.4513	0.5896	0.5988
FeedbackTrust [22]	0.3764	0.4684	0.5433	0.5469
Influence-based [9]	0.3859	0.4686	0.5394	0.5446
SoRec [19]	0.3276	0.4127	0.6168	0.6204
SoReg [20]	0.2985	0.3537	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**

	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%

Effectiveness in Ranking Feeds/Tweets



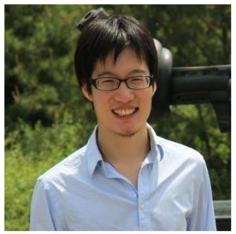
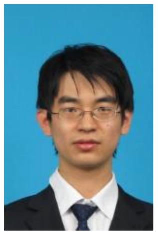
Renren



Tencent Weibo

	Renren	Tencent Weibo
Top-5 Precision	+21.7%	+12.3%
Top-10 Precision	+10.8%	+6.85%

Questions?



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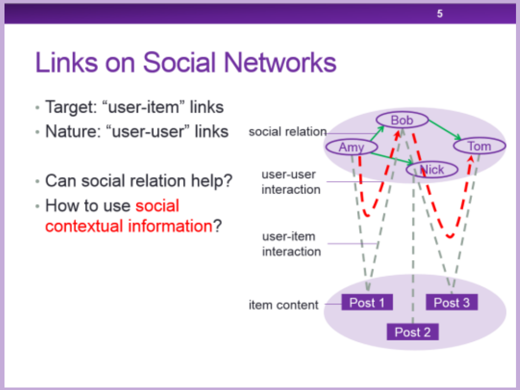
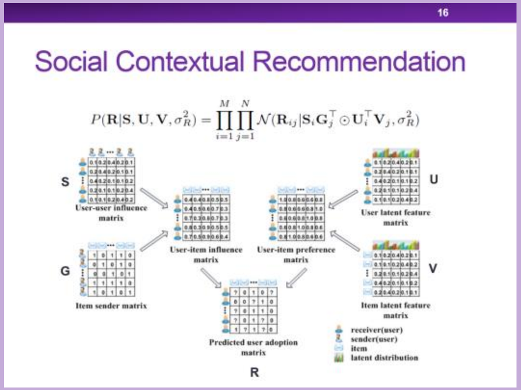
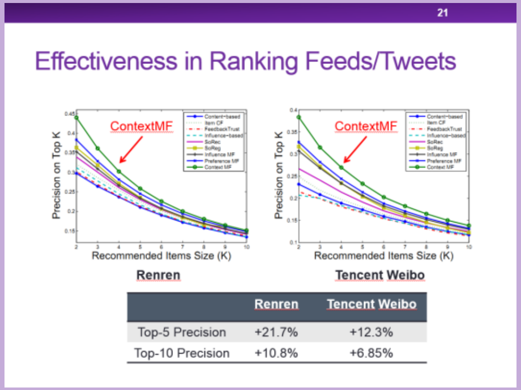






SCALABLE RECOMMENDATION WITH SOCIAL CONTEXTUAL INFORMATION

Meng Jiang

Joint work with Peng Cui, Fei Wang, Wenwu Zhu and Shiqiang Yang

TKDE 2014 (IF=1.815, 5-year IF=2.573)

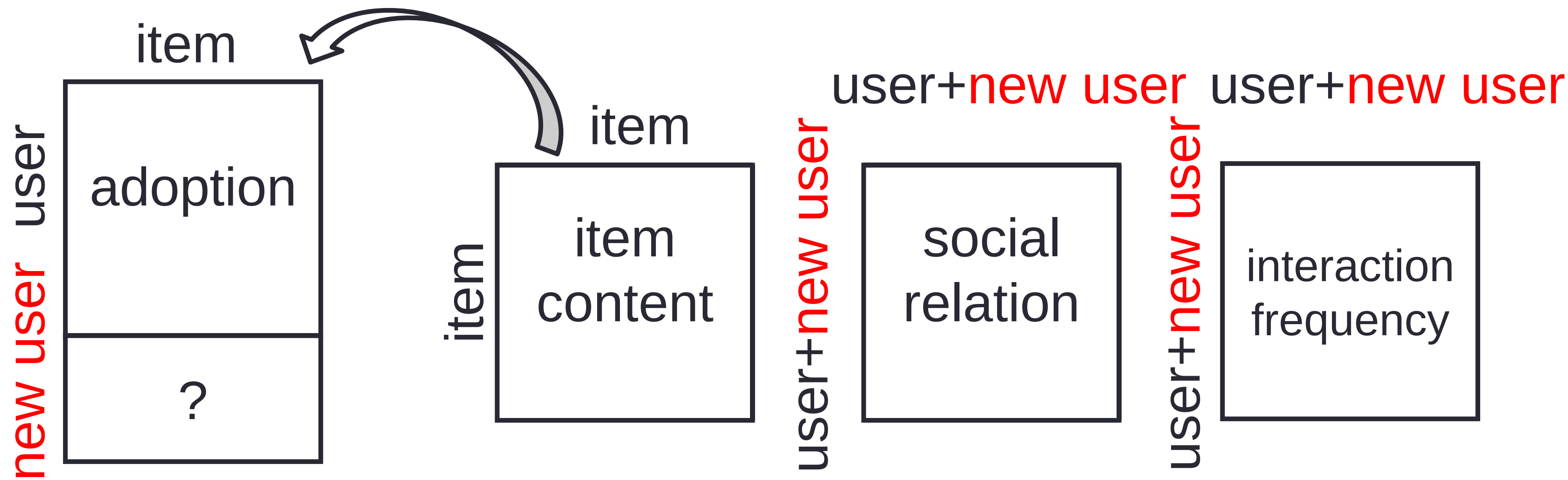
Our Goals

- Given: Links on social networks
- Find: A social recommendation framework that fast and best fit adopting behaviors

- Goals:
  - G1. Understand user intention of adoption
  - G2. A scalable framework for recommendation
  - G3. Fast predict the missing “user-item” links

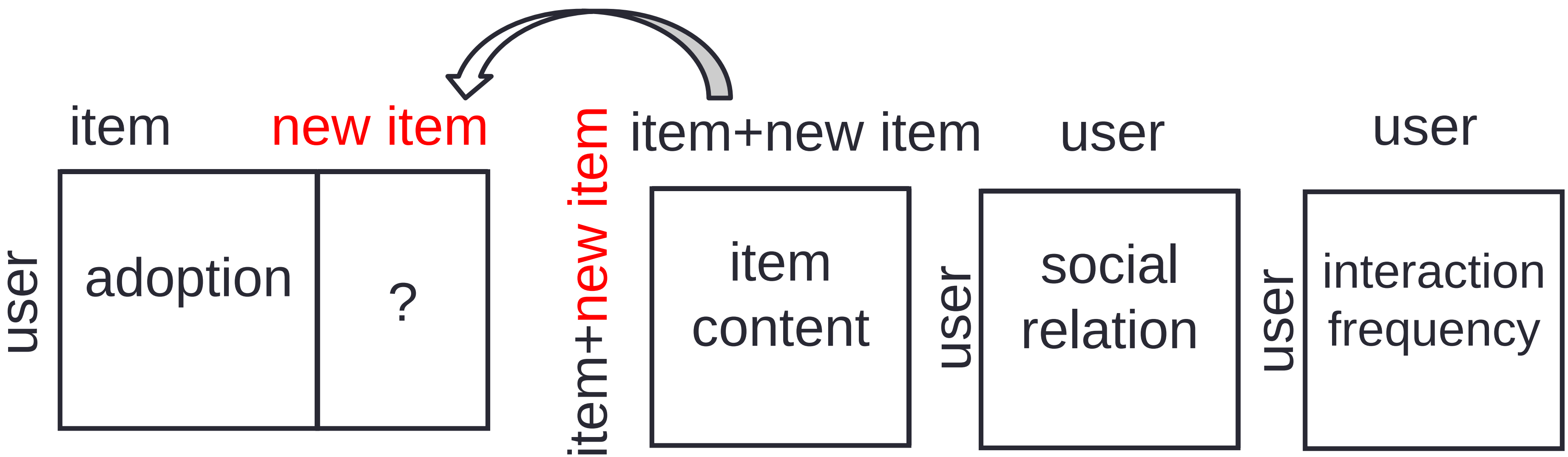
New Users Coming

	Old *N* items	**New *ΔN* items**
Old *M* users	Done! $O(k^2L(M+N)^2)$	C $\mathcal{J}_{\Delta V} = \lVert\mathbf{\Delta C} - \mathbf{\Delta V}^\top\mathbf{V}\rVert_F^2, \frac{\partial\mathcal{J}}{\partial\mathbf{\Delta V}} = -2\mathbf{V}\mathbf{\Delta C}^\top + O(\mathbf{\Delta V})$
New *ΔM* users	$\mathcal{J}_{\Delta S} = \lVert\mathbf{\Delta F} - \mathbf{\Delta S}\rVert_F^2, \quad \frac{\partial\mathcal{J}}{\partial\mathbf{\Delta S}} = -2\mathbf{\Delta F} + O(\mathbf{\Delta S})$ $\mathcal{J}_{\Delta U} = \lVert\mathbf{\Delta W} - \mathbf{\Delta U}^\top\mathbf{U}\rVert_F^2, \quad \frac{\partial\mathcal{J}}{\partial\mathbf{\Delta U}} = -2\mathbf{U}\mathbf{\Delta W}^\top + O(\mathbf{\Delta U})$ $O(k^2L\Delta MM) << O(k^2LM(M+N))$	Sorry… Cold-start problem



New Items Coming

	Old *N* items	New *ΔN* items
Old *M* users	Done! O(k²L(M+N)²)	$\mathcal{J}_{\Delta V} = \|\|\mathbf{\Delta C} - \mathbf{\Delta V}^\top \mathbf{V}\|\|_F^2, \frac{\partial \mathcal{J}}{\partial \mathbf{\Delta V}} = -2\mathbf{V}\mathbf{\Delta C}^\top + O(\mathbf{\Delta V})$ $O(k^2 L \Delta N N) << O(k^2 L N(M+N))$
New *ΔM* users	$\mathcal{J}_{\Delta S} = \|\|\mathbf{\Delta F} - \mathbf{\Delta S}\|\|_F^2, \quad \frac{\partial \mathcal{J}}{\partial \mathbf{\Delta S}} = -2\mathbf{\Delta F} + O(\mathbf{\Delta S})$ $\mathcal{J}_{\Delta U} = \|\|\mathbf{\Delta W} - \mathbf{\Delta U}^\top \mathbf{U}\|\|_F^2, \quad \frac{\partial \mathcal{J}}{\partial \mathbf{\Delta U}} = -2\mathbf{U}\mathbf{\Delta W}^\top + O(\mathbf{\Delta U})$ $O(k^2 L \Delta M M) << O(k^2 L M(M+N))$	Sorry… Cold-start problem

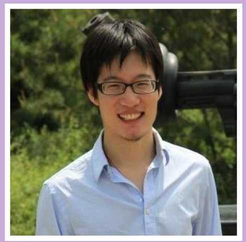


Efficiency in Incremental Data

- Better than SoReg [Ma et al. WSDM 2011]
- A little bit worse than offline learning (re-training)
- Save time from hours to minutes when (M,N ~ million) and (ΔM,ΔN ~ thousand)

Dataset	RMSE (smaller is better)			ERR (bigger is better)			Time cost	
	$SoReg$	$\Delta ContextMF$	$ContextMF^{\Delta}$	$SoReg$	$\Delta ContextMF$	$ContextMF^{\Delta}$	$\Delta ContextMF$	$ContextMF^{\Delta}$
RΔM1000	0.342	0.263	0.257	0.555	0.610	0.636	172s	41.7h
RΔM10000	0.502	0.464	0.444	0.481	0.542	0.559	1610s	41.7h
TΔM1000	0.168	0.122	0.105	0.652	0.764	0.783	54.2s	2.42h
TΔM10000	0.342	0.333	0.317	0.534	0.611	0.651	531s	2.42h
RΔN1000	0.335	0.276	0.276	0.570	0.663	0.680	97.3s	41.7h
RΔN10000	0.546	0.478	0.465	0.514	0.587	0.609	941s	41.7h
TΔN1000	0.218	0.192	0.173	0.726	0.824	0.864	17.8s	2.42h
TΔN10000	0.427	0.376	0.355	0.658	0.720	0.751	160s	2.42h

Questions?

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