



Combining Ratings, Social Relations, and Reviews for Recommendation

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RSs are Ubiquitous



- Books at Amazon
- Movies at Netflix
- People at OkCupid

Recommended for You

These recommendations are based on [items you own](#) and [what you've viewed](#).
 view: **All** | [New Releases](#) | [Coming Soon](#)

1.  **Applied Predictive Modeling**
 by Max Kuhn (September 15, 2010)
 Average Customer Review: **★★★★**
 Usually ships in 1 to 3 weeks
List Price: \$89.95
Price: \$65.81 



MATCHES TESTS DISCUSSION JOIN NOW! **FREE AND FUN! JOINING TAKES 60 SECONDS!**

Today's Most Popular! (Jul 18)

2. 



NETFLIX
Netflix Prize
 Home Rules Leaderboard Register Update Submit Downlo
 NETFLIX
 Browse Recommendations Friends Queue Buy DVDs
 Home Genres New Releases Previews Netflix Top 100 Crit
Movies For You
 username password
 stay logged in
 You really liked it...
 Now own for just \$5.99
 Shop as low
 Original art

Online Dating!

OkCupid is a truly free online dating site, and it's powered by a matching system *you invent*. Joining takes 60 seconds and the matching starts immediately.

My Relationship Status
 I'm single

Already have an account? [Sign in](#)



Recommendation as Rating Prediction



• *Rec*: Users x Items
→ Ratings

• Predict **unknown** ratings from observed data

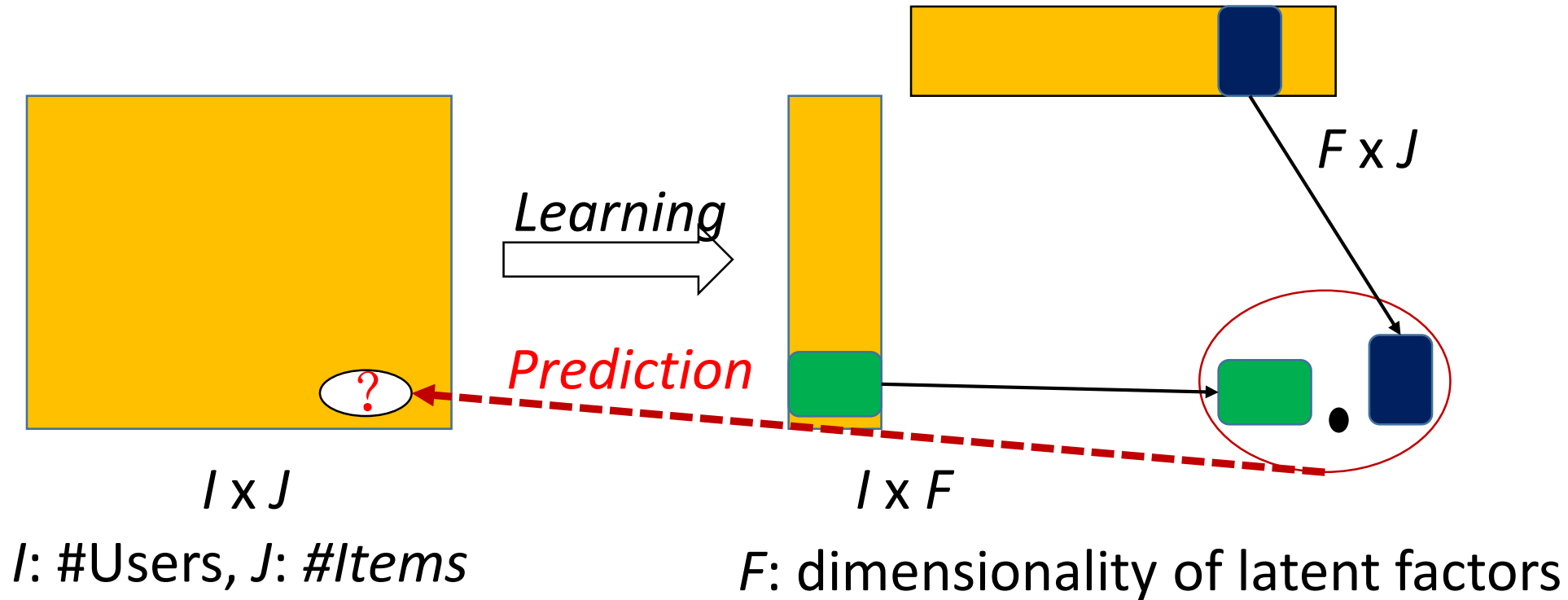
	4	5	6	7	8	9
	2	?	2	?	5	?
	5	?	4	?	?	1
	?	?	5	?	2	?
	?	1	?	5	?	?
	?	5	?	1	?	4



Typical Model: Probabilistic Matrix Factorization (PMF)



- Low dimensional representations of users and of items



Salakhutdinov & Mnih, Probabilistic matrix factorization, NIPS 2008



Issues of PMF



- Sparse rating matrix, e.g.,
 - Epinions: 0.022%
 - Ciao: 0.11%
- Cold-start users & items
 - Have no or few ratings

Statistics	Epinions	Ciao
# of Users	49,454	7,340
# of Items	74,154	22,472
# of Ratings/Reviews	790,940	183,974
# of Social Relations	434,680	112,942
# of Words	2,246,837	28,874,000
Rating Density	0.00022	0.0011
Social Density	0.00018	0.0021
Ave. Words Per Item	30.3	1284.9



One Research Line to Address the Issues



- Topic MF: Integrating item reviews into ratings
 - Item reviews justify the ratings

Oliviunea...  **Rating** “ iPhone 6 16GB - A jump into the best Smartphone available place. ” 17.11.2014


[Add to my Circle of Trust](#)
[Subscribe to reviews](#)
About me: Exams coming up next, sorry for my absence.
Member since: 12.10.2014
Reviews: 30

I am a tech freak, I have owned every iPhone this, but I also owned almost every flagship / rarely keep smartphones more than 6 months or sell them and put a little extra so I can buy I bought about 3 weeks ago. I used to have the everything about it, it was small and beautiful, had the opportunity to exchange it for an iPhone photos and videos I disliked the design bigger phone and hated how I had to walking, always in need for 2 hands was one

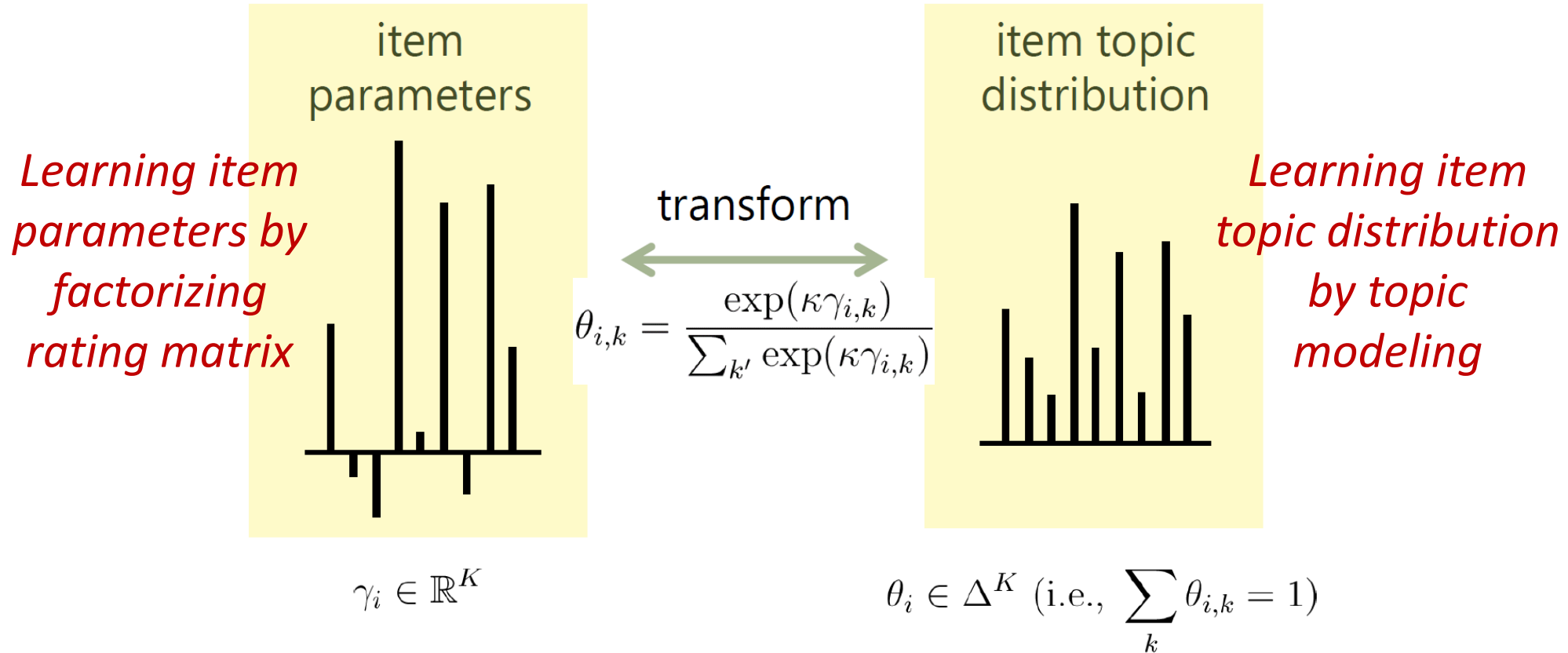
ciao!
amazon.com



One Research Line (cont')



- Typical model: Hidden factors and hidden topics (HFT)



McAuley & Leskovec, Hidden factors and hidden topics, RecSys 2013



Another Research Line to Address the Issues



- Social MF: Integrating social relations into ratings
 - The rating behavior of users is influenced by their friends

Oliviunea...
Rating: ★★★★★
Add to my Circle of Trust
Subscribe to reviews
About me: Exams coming up next, sorry for my absence.
Member since: 12.10.2014
Reviews: 30
Members who trust: 17

ciao!

Hgn Nju
Timeline About Friends 33 Photos More
Friends
All Friends 33 Recently Added 1 Following
Social Relations
Mingkun Gao 158 friends
Jie Tang 917 friends
Chenyan Xiong 476 friends
Jun Zhu 583 friends

facebook

Social Relations



Another Research Line (cont')



- Typical model: Local and global recommender (LOCABAL)

Exploiting global social context by user reputation

$$\begin{aligned}
 & \min_{\mathbf{U}, \mathbf{V}, \mathbf{H}} \sum_{\langle u_i, v_j \rangle \in \mathcal{O}} w_i (\mathbf{R}_{ij} - \mathbf{u}_i^\top \mathbf{v}_j)^2 \quad \text{Exploiting ratings by learning latent representations of users and of items} \\
 & + \alpha \sum_{i=1}^n \sum_{u_k \in \mathcal{N}_i} (\mathbf{S}_{ik} - \mathbf{u}_i^\top \mathbf{H} \mathbf{u}_k)^2 \quad \text{Exploiting local social context by learning latent social representations} \\
 & + \lambda (\|\mathbf{U}\|_F^2 + \|\mathbf{V}\|_F^2 + \|\mathbf{H}\|_F^2),
 \end{aligned}$$

Tang et al., Exploiting local and global social context for recommendation, IJCAI 2013



Issues of Topic MF and Social MF



- Item reviews and social relations are both useful
 - Demonstrated by HFT and LOCABAL respectively
- Topic MF, e.g., HFT
 - ignores the social relations
- Social MF, e.g., LOCABAL
 - ignores the item reviews




Combining Ratings, Social Relations, and Reviews for Recommendation



- Item reviews and social relations are both useful for improving rating prediction

OliviuNea...

★★★★★
Rating



[Add to my Circle of Trust](#)
[Subscribe to reviews](#)

About me: Exams coming up next, sorry for my absence.

Member since: 12.10.2014
Reviews: 30
Members who trust: 17

Social Relations

“ iPhone 6 16GB - A jump into the best Smartphone available place. ” 17.11.2014

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Review

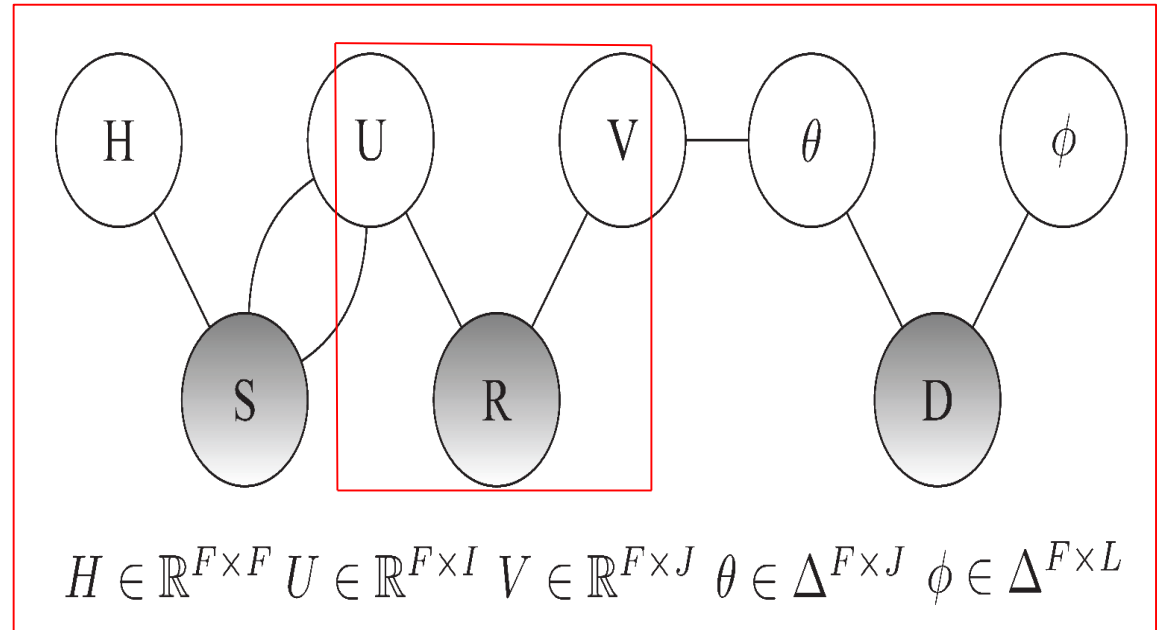




Modelling Three Kinds of Data Sources



- **Key:** connecting relations and reviews through ratings
 - For rating source, learning latent representations of users and of items

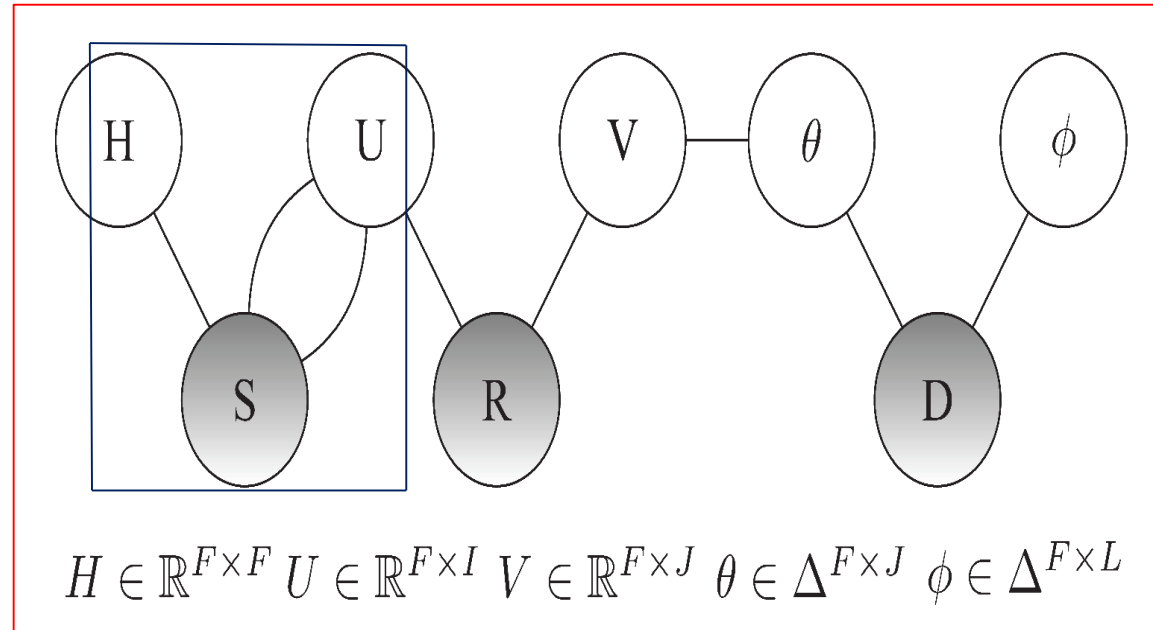




Modelling Three Kinds of Data Sources



- **Key:** connecting relations and reviews through ratings
 - For rating source, learning latent representations of users and of items
 - For social relation source, learning latent social representations of users and their social relation matrix

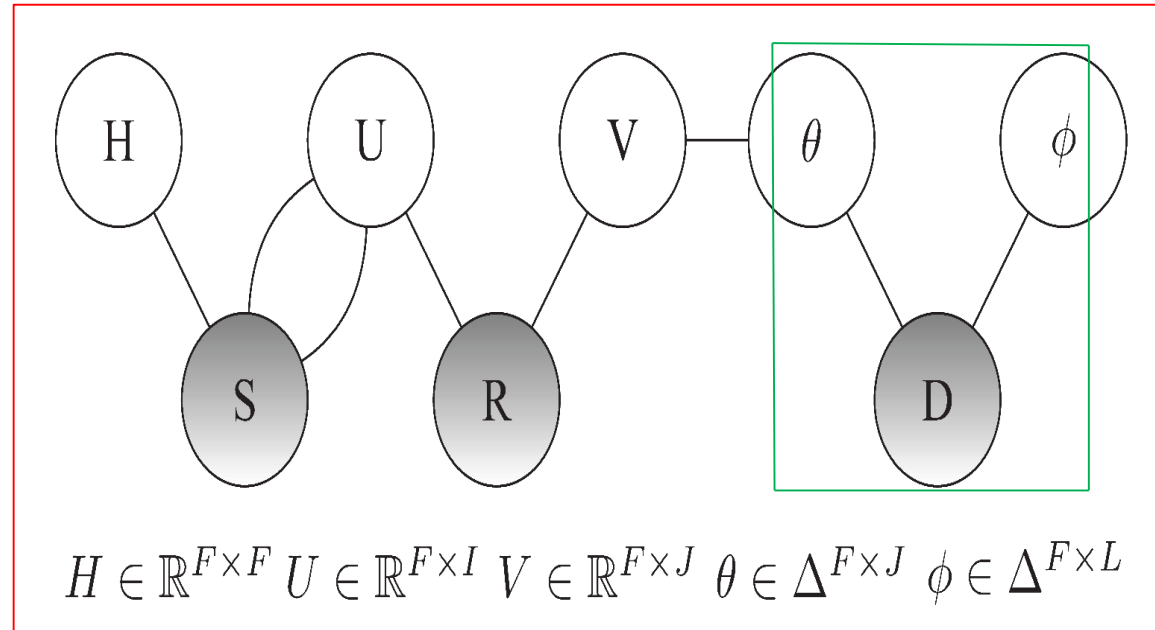




Modelling Three Kinds of Data Sources



- **Key:** connecting relations and reviews through ratings
 - For rating source, learning latent representations of users and of items
 - For social relation source, learning latent social representations of users and their social relation matrix
 - For item reviews, learning topic distributions (and word distributions)

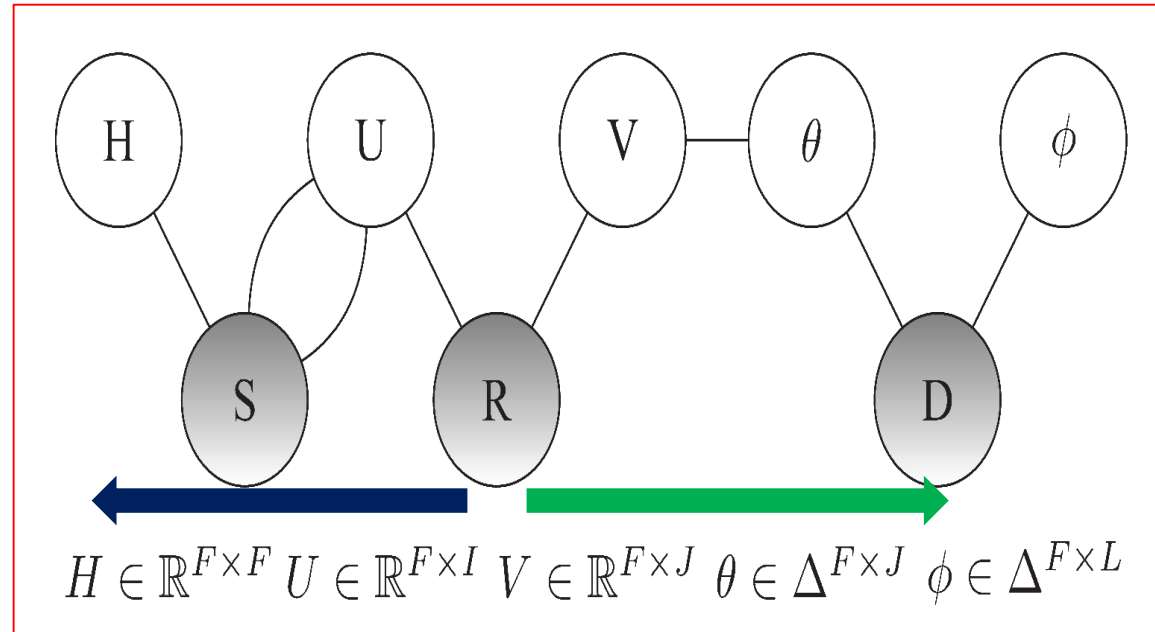




Modelling Three Kinds of Data Sources



- **Key:** connecting **relations** and **reviews** through **ratings**
 - For rating source, learning latent representations of users and of items
 - For social relation source, learning latent social representations of users and their social relation matrix
 - For item reviews, learning topic distributions and word distributions





MR3: A Model of Ratings, Reviews and Relations



$$\begin{aligned} \mathcal{L}(\Theta, \Phi, z, \kappa) \triangleq & \sum_{R_{i,j} \neq 0} W_{i,j} \underbrace{(R_{i,j} - \hat{R}_{i,j})^2}_{\text{Exploiting ratings}} \\ & - \lambda_{\text{rev}} \sum_{d=1}^J \sum_{n \in N_d} \underbrace{(\log \theta_{z_{d,n}} + \log \phi_{z_{d,n}, w_{d,n}})}_{\text{Exploiting reviews}} \\ & + \lambda_{\text{rel}} \sum_{T_{i,k} \neq 0} \boxed{C_{i,k}} \underbrace{(S_{i,k} - U_i^T H U_k)^2}_{\text{Exploiting social relations}} + \lambda \Omega(\Theta), \end{aligned}$$

here parameters $\Theta = \{U, V, H\}$ are associated with ratings and social relations, parameters $\Phi = \{\theta, \phi\}$ associated with reviews.



By-product of MR3: eSMF (extended Social MF)

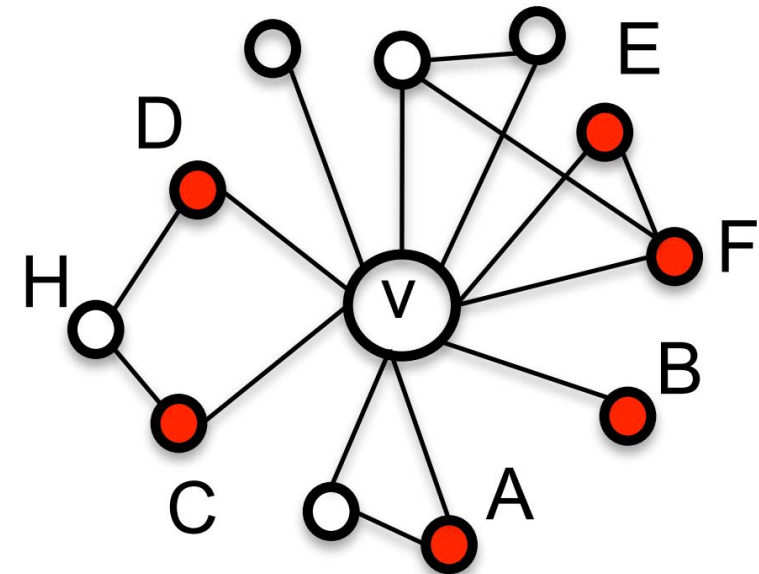


- Graph structure of neighbors captures social influence locality, i.e., user behaviors are mainly influenced by close/direct friends in their ego networks

$$\min_{U, V, H} \sum_{R_{i,j} \neq 0} W_{i,j} (R_{i,j} - \hat{R}_{i,j})^2 + \lambda \sum_{T_{i,k} \neq 0} C_{i,k} (S_{i,k} - U_i^T H U_k)^2 + \lambda \Omega(\Theta)$$

The trust values

$$C_{ik} = \sqrt{d_{u_k}^- / (d_{u_i}^+ + d_{u_k}^-)},$$



Ma et al., SoRec: Social Recommendation Using Probabilistic Matrix Factorization, CIKM 2008

Zhang et al., Social influence locality for modeling retweeting behaviors, IJCAI 2013



Learning Parameters



- Alternating two steps
 - Topic assignments $z_{d,n}$ for each word in reviews corpus are fixed; then we update the terms Θ , Φ , and κ by gradient descent
 - Parameters associated with reviews corpus θ and ϕ are fixed; then sample $z_{d,n}$ by iterating through all docs and each word within

$$\begin{aligned} &\text{update } \Theta^{\text{new}}, \Phi^{\text{new}}, \kappa^{\text{new}} = \arg \min_{\Theta, \Phi, \kappa} \mathcal{L}(\Theta, \Phi, \kappa, z^{\text{old}}); \\ &\text{sample } z_{d,n}^{\text{new}} \text{ with probability } p(z_{d,n}^{\text{new}} = f) = \phi_{f, w_{d,n}}^{\text{new}}. \end{aligned} \tag{1}$$



Gradient descent



- Alternating two steps
 - Topic assignments $z_{d,n}$ for each word in reviews corpus are fixed; then we update the terms Θ , Φ , and κ by **gradient descent**
 - Parameters associated with reviews corpus θ and ϕ are fixed; then sample $z_{d,n}$ by iterating through all docs and each word within

$$\begin{aligned} \frac{1}{2} \frac{\partial \mathcal{L}}{\partial U_i} &= \sum_{j:R_{i,j} \neq 0} W_{i,j} (\hat{R}_{i,j} - R_{i,j}) V_j + \lambda U_i \\ &+ \lambda_{\text{rel}} \sum_{k:T_{k,i} \neq 0} C_{i,k} (U_k^T H U_i - S_{i,k}) H^T U_k \\ &+ \lambda_{\text{rel}} \sum_{k:T_{i,k} \neq 0} C_{k,i} (U_i^T H U_k - S_{i,k}) H U_k. \end{aligned}$$

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial V_j} &= 2 \sum_{i:R_{i,j} \neq 0} W_{i,j} (\hat{R}_{i,j} - R_{i,j}) U_i \\ &- \lambda_{\text{rev}} \kappa \left(M_j - \frac{m_j}{z_j} \exp(\kappa V_j) \right) + 2\lambda V_j. \end{aligned}$$

$$\frac{1}{2} \frac{\partial \mathcal{L}}{\partial H} = \lambda_{\text{rel}} \sum_{T_{i,k} \neq 0} C_{i,k} (U_i^T H U_k - S_{i,k}) U_i U_k^T + \lambda H.$$

$$\frac{\partial \mathcal{L}}{\partial \psi_{fw}} = -\lambda_{\text{rev}} \left(M_{fw} - \frac{m_f}{z_f} \exp(\psi_{fw}) \right).$$

$$\frac{\partial \mathcal{L}}{\partial \kappa} = -\lambda_{\text{rev}} \sum_{j,f} V_{jf} \left(M_{jf} - \frac{m_j}{z_j} \exp(\kappa V_{jf}) \right).$$



Datasets



- Epinions and Ciao

- <http://www.public.asu.edu/~jtang20/>

Statistics	Epinions	Ciao
# of Users	49,454	7,340
# of Items	74,154	22,472
# of Ratings/Reviews	790,940	183,974
# of Social Relations	434,680	112,942
# of Words	2,246,837	28,874,000
Rating Density	0.00022	0.0011
Social Density	0.00018	0.0021
Ave. Words Per Item	30.3	1284.9



Metric and Code



- RMSE (root-mean-square error)
 - The lower, the better

$$RMSE_{\mathcal{T}} = \sqrt{\sum_{(u_i, v_j) \in \mathcal{T}} (R_{i,j} - \hat{R}_{i,j})^2 / |\mathcal{T}|}$$

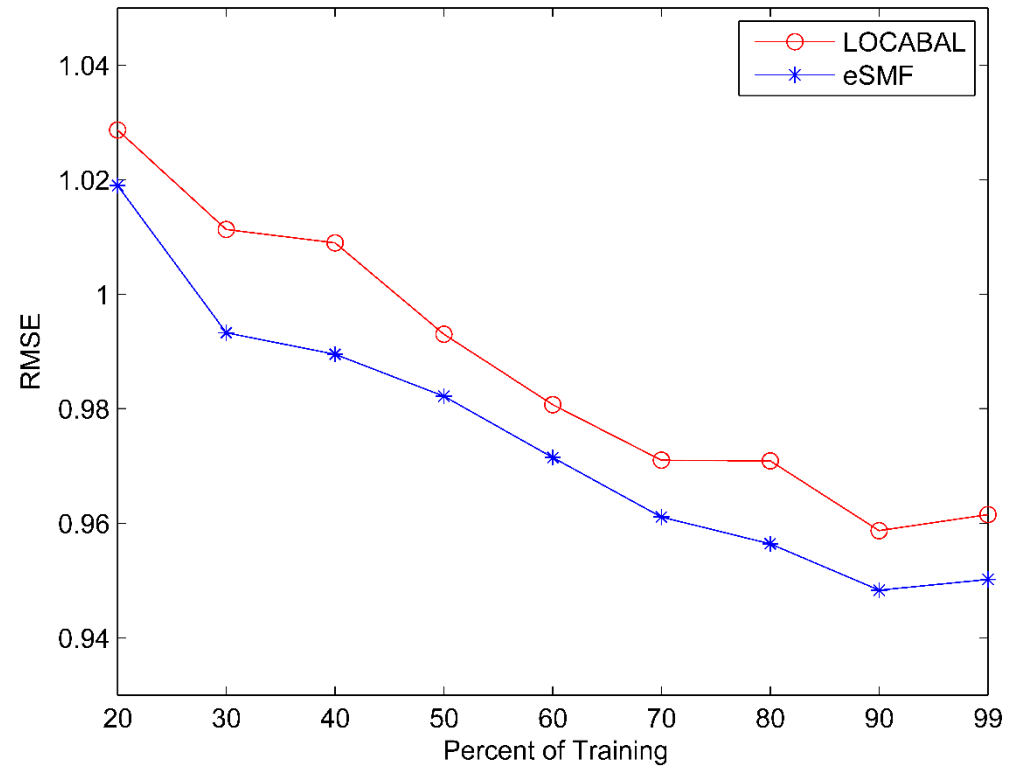
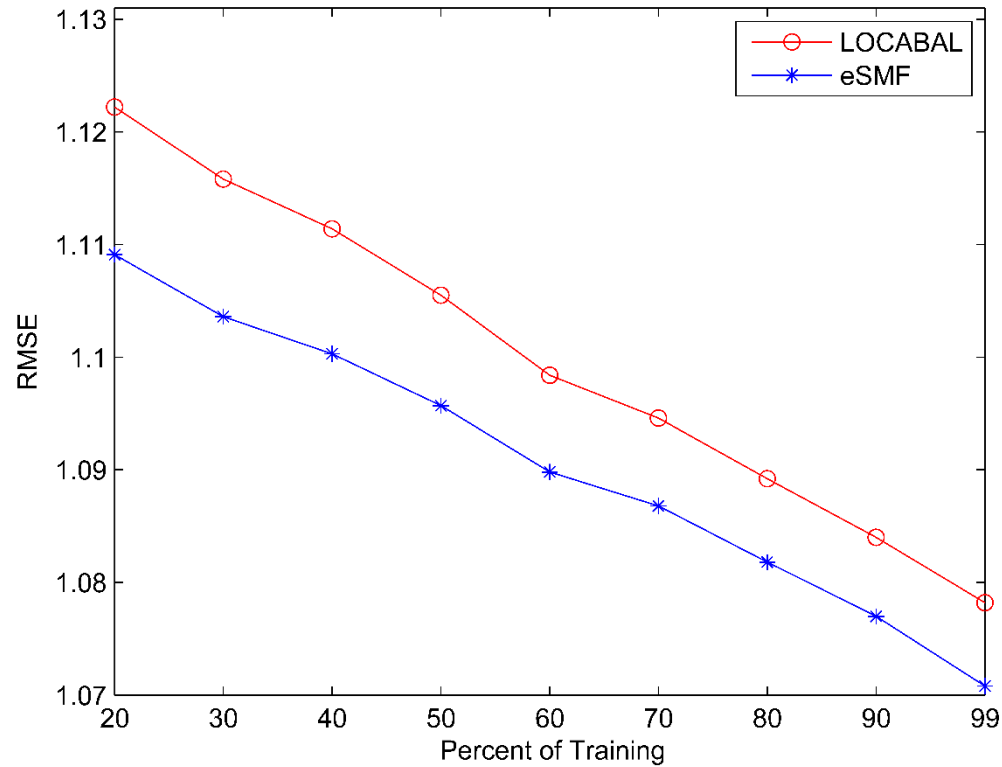
- PMF
 - <http://www.cs.toronto.edu/~rsalakhu/BPMF.html>
- HFT
 - <http://cseweb.ucsd.edu/~jmcauley/>



Comparing Social MF



• eSMF vs. LOCABAL



Left: Epinions; Right: Ciao



Comparing Different Recommender Systems



- MR3 vs. PMF, HFT, and LOCABAL (F = 10)

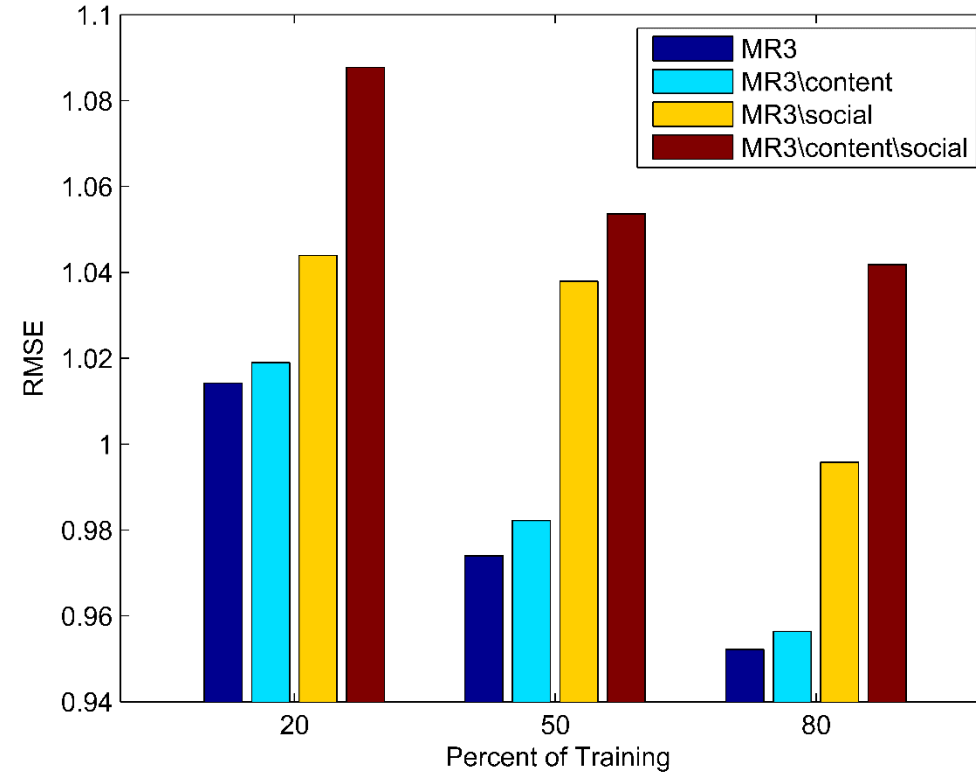
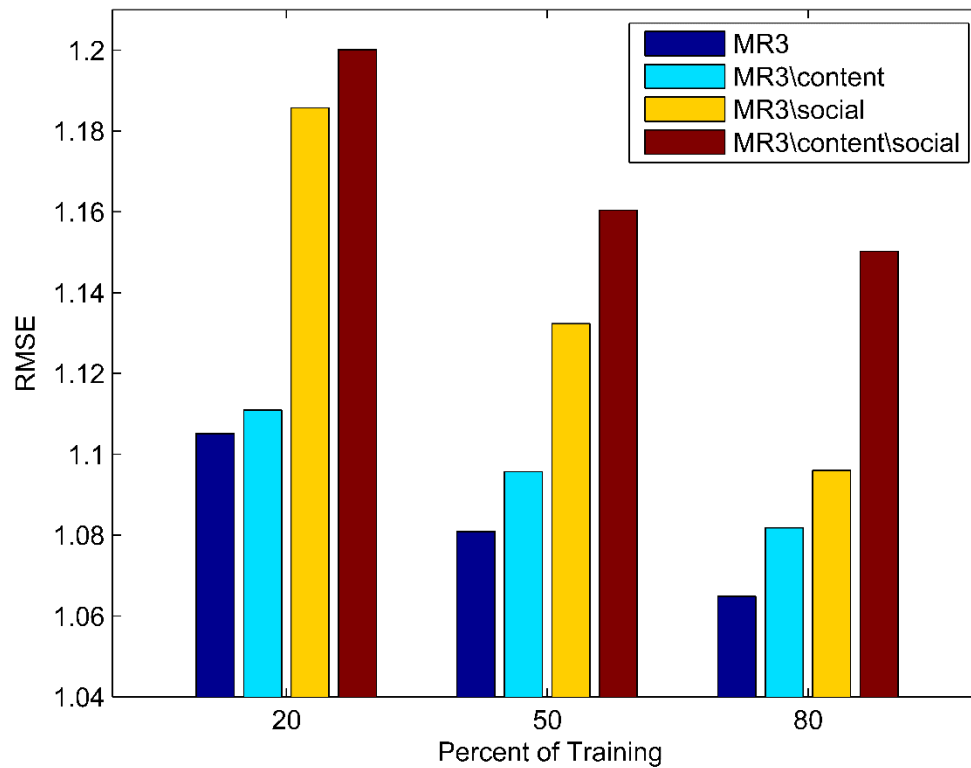
Datasets	Training	Methods					Improvement of MR3 vs.		
		Mean	PMF	HFT	LOCABAL	MR3	PMF	HFT	LOCABAL
Epinions	20%	1.2265	1.2001	1.1857	1.1222	1.1051	8.60%	7.29%	1.55%
	50%	1.2239	1.1604	1.1323	1.1055	1.0809	7.35%	4.76%	2.28%
	80%	1.2225	1.1502	1.0960	1.0892	1.0648	8.02%	2.93%	2.29%
	90%	1.2187	1.1484	1.0867	1.0840	1.0634	7.99%	2.19%	1.94%
Ciao	20%	1.1095	1.0877	1.0439	1.0287	1.0142	7.25%	2.93%	1.43%
	50%	1.0964	1.0536	1.0379	0.9930	0.9740	8.17%	6.56%	1.95%
	80%	1.0899	1.0418	0.9958	0.9709	0.9521	9.42%	4.59%	1.97%
	90%	1.0841	1.0391	0.9644	0.9587	0.9451	9.95%	2.04%	1.44%
Average							8.34%	4.16%	1.86%



Impact of Reviews and Social Relations



- MR3 compared with its three components (F = 10)



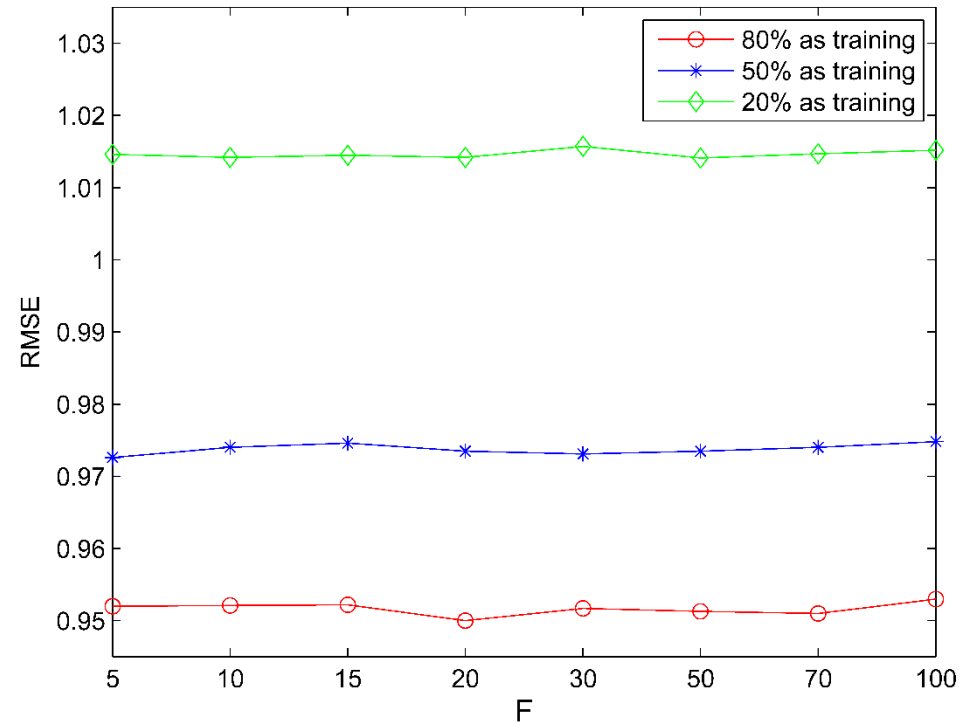
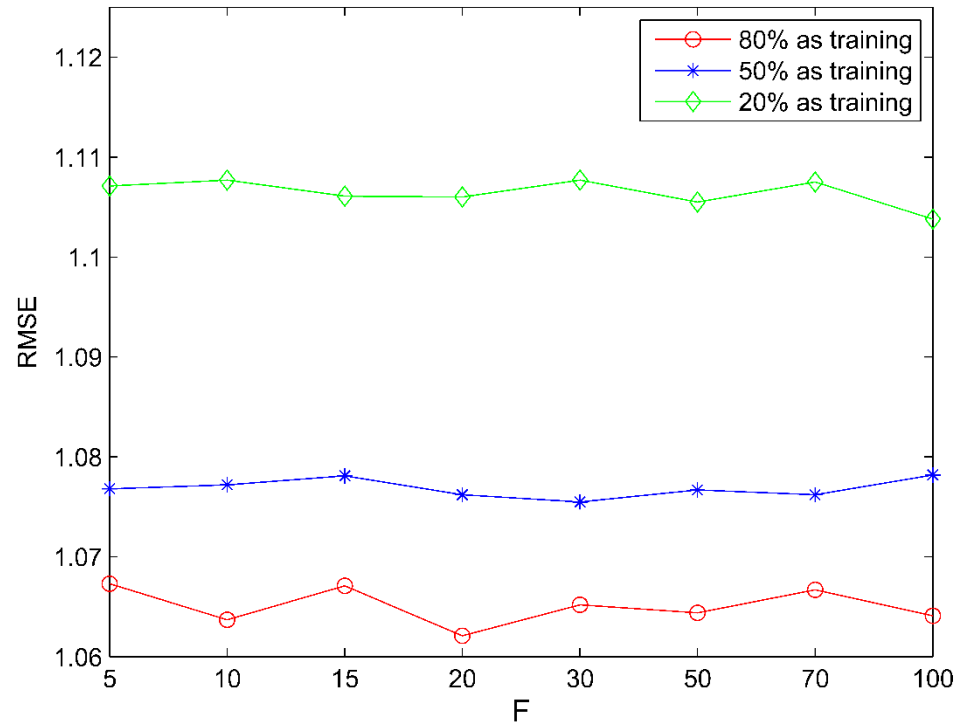
Left: Epinions; Right: Ciao



Sensitivity to Parameters



- F: the number of latent factors; Default: 10



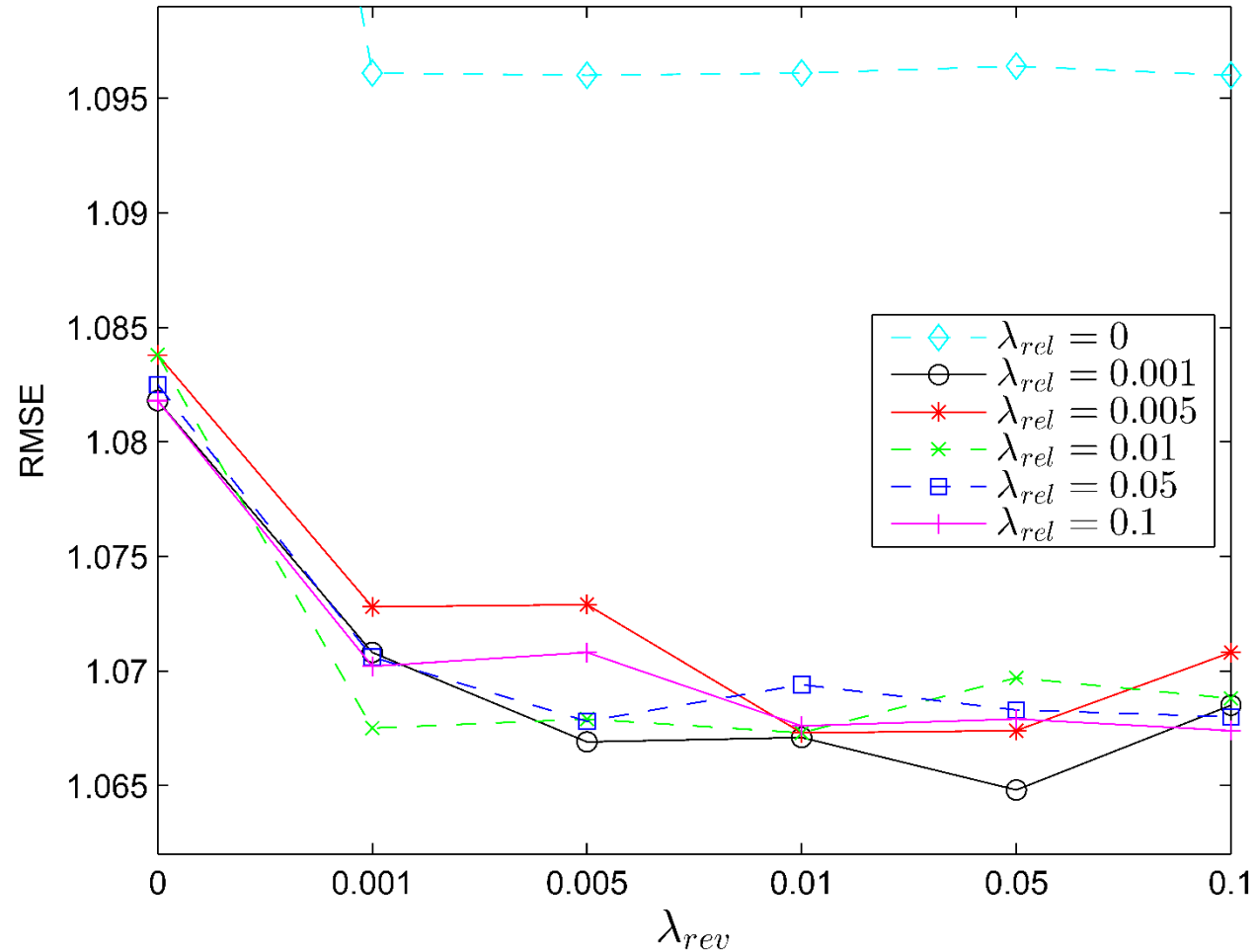
Left: Epinions; Right: Ciao



Sensitivity to Parameters (cont')



- λ_{rel} : controls the contribution from social *relations*
- λ_{rev} : controls the contribution from *reviews*
- Default: 0.001, 0.05





Conclusions



- A novel framework to exploit ratings, social relations, and reviews simultaneously for recommendation
- An advanced method to exploit ratings and social relations more tightly by capturing the graph structure of neighbors
- Significant improvements over the state of the art methods on the rating prediction task



Future Works



- Implicit feedback
- Temporal dynamics
- Number of hidden topics in reviews different from that of latent factors in ratings



References



- Salakhutdinov & Mnih, *Probabilistic matrix factorization*, NIPS 2008
- McAuley & Leskovec, *Hidden factors and hidden topics*, RecSys 2013
- Ma et al., *SoRec: Social Recommendation Using Probabilistic Matrix Factorization*, CIKM 2008
- Tang et al., *Exploiting local and global social context for recommendation*, IJCAI 2013
- Zhang et al., Social influence locality for modeling retweeting behaviors, IJCAI 2013
- **Hu et al., *A Synthetic Approach for Recommendation: Combining Ratings, Social Relations, and Reviews*, to appear in IJCAI 2015**



Thanks

Q&A