



# Synthetic Recommendation and Its Extension

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# Outline



- Part I. Synthetic Recommendation: Combining Ratings, Social Relations, and Reviews
  - Based on the published work of IJCAI-15, i.e., the MR3 model
- Part II. An Extension: Incorporating Implicit Feedback from Ratings
  - Based on the submitted work of TKDE-16, i.e., the MR3++ model
- Part III. Future Work
  - An idea: Further analysis from the cold-start perspective



## Part I

Synthetic Recommendation (or the MR3 model):  
Combining Ratings, Social Relations, and Reviews



# RSs are Ubiquitous



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

## Recommended for You

[click here.](#))

These recommendations are based on [items you own](#) and

view: **All** | [New Releases](#) | [Coming Soon](#)

1. **LOOK INSIDE!** **Applied Predictive Modeling** by Max Kuhn (September 15, 2013)  
Average Customer Review: **★★★★☆**  
Usually ships in 1 to 3 weeks  
**List Price:** \$89.95  
**Price:** **\$65.81**  
[54 used & new from](#)

## okcupid

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

Today's Most Popular! ( Jul 18 )



## Online Dating!

OkCupid is a truly free online dating site, and it's powered by a matching system

## News

U.S. edition

Modern

Personalize

## Top Stories



## Glenn Frey, a Founding Member of the Eagles, Dies at 67

New York Times - 57 minutes ago

Glenn Frey, the guitarist, singer and songwriter who co-founded the Eagles, whose country-tinged, melodic rock tunes, wistful love ballads, philosophical anthems, observations of the outlaw life and testaments to the wages of decadence made it perhaps ...

NETFLIX

# Netflix Prize

Home Rules Leaderboard Register Update Submit Download

Browse Recommendations Friends Queue Buy DVDs

Home Genres New Releases Previews Netflix Top 100 Crit

## Movies For You

The following movies were based on your interest in: [Dr. Columbo: Season 1](#)

**The Big One**

**You really liked it...**

Now only for just \$5.99



# Recommendation as Rating Prediction



- *Rec*: Users x Items  
→ Ratings

- Predict **unknown** ratings from observed data

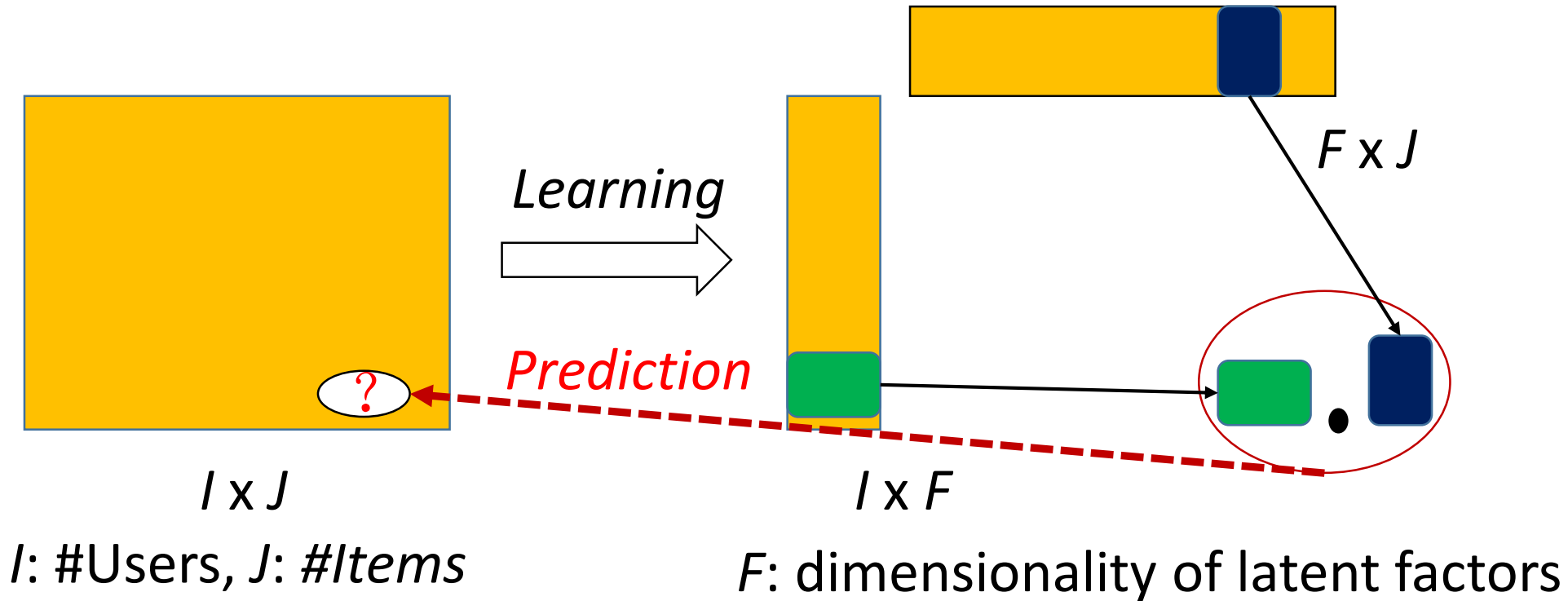
	4	5	6	7	8	9
	2	?	2	?	5	?
	5	?	4	?	?	1
	?	?	5	?	2	?
	?	1	?	5	?	?
	?	5	?	1	?	4



# Typical Model: Probabilistic Matrix Factorization (PMF)



- Low dimensional representations of users and of items





# 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

 **ciao!**

[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

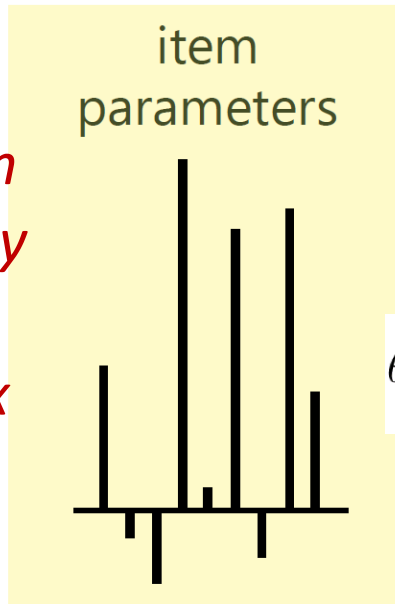
I am a tech freak, I have owned every iPhone this, but I rarely keep **amazon.com** or sell the  
I bought about 3 weeks ago. I used to have the everything about it, it was small and beautiful, had the opportunity to exchange it for an iPhone photos and videos I disliked the design of the bigger phone and hated how I had problems walking, always in need for 2 hands was one





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

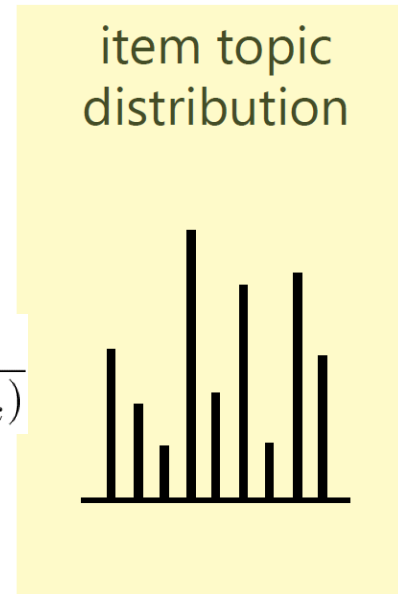
*Learning item parameters by factorizing rating matrix*



$$\gamma_i \in \mathbb{R}^K$$

transform

$$\theta_{i,k} = \frac{\exp(\kappa\gamma_{i,k})}{\sum_{k'} \exp(\kappa\gamma_{i,k})}$$



*Learning item topic distribution by topic modeling*

$$\theta_i \in \Delta^K \text{ (i.e., } \sum_k \theta_{i,k} = 1)$$



# Another Research Line to Address the Issues



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

**Rating**

**ciao!**

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**

**facebook**

**Social Relations**

 Mingkun Gao 158 friends	 Jie Tang 917 friends
 Chenyan Xiong 476 friends	 Jun Zhu 583 friends





# Issues of Topic MF and Social MF



- Item reviews and social relations are both useful
  - Demonstrated by HFT and LOCABAL, respectively
- One research line can benefit from another
  - Topic MF, e.g., HFT: ignores the social relations
  - Social MF, e.g., LOCABAL: ignores the item reviews



# Our Proposed Model: Combining Ratings, Reviews and Social Relations



- Item reviews and social relations are both useful for improving rating prediction
- So, put all of them altogether

**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 **Review**

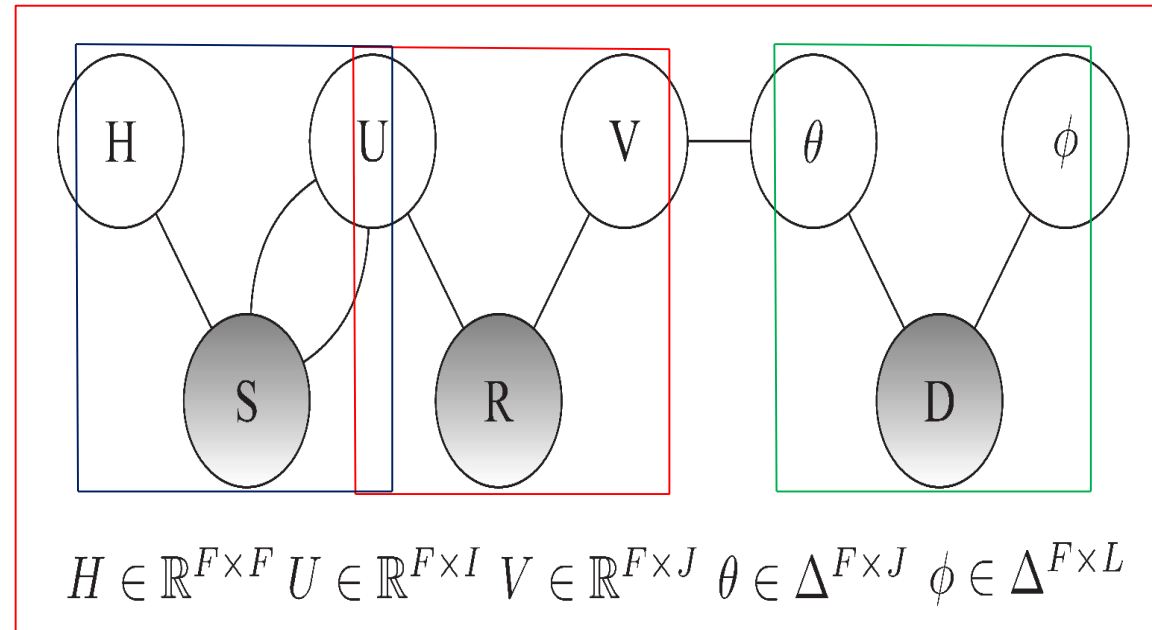
I am a tech freak, I have owned every iPhone this, but I also owned almost every flagship A rarely keep smartphones more than 6 months or sell them and put a little extra so I can buy I bought about 3 weeks ago. I used to have th everything about it, it was small and beautiful, had the opportunity to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



# Challenge: Jointly Modelling Three Kinds of Data Sources



- *Key idea*: 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



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

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



# Model Learning



- Alternating two steps
  - Topic assignments  $z_{d,n}$  for each word in reviews corpus are fixed; then we update the terms  $\Theta$ ,  $\Phi$ , and  $\kappa$  by gradient descent
  - Parameters associated with reviews corpus  $\theta$  and  $\phi$  are fixed; then sample  $z_{d,n}$  by iterating through all docs and each word within

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





# Gradients



- Alternating two steps
  - Topic assignments  $z_{d,n}$  for each word in reviews corpus are fixed; then we update the terms  $\Theta$ ,  $\Phi$ , and  $\kappa$  by gradient descent
  - Parameters associated with reviews corpus  $\theta$  and  $\phi$  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
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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 Different Recommender Systems



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

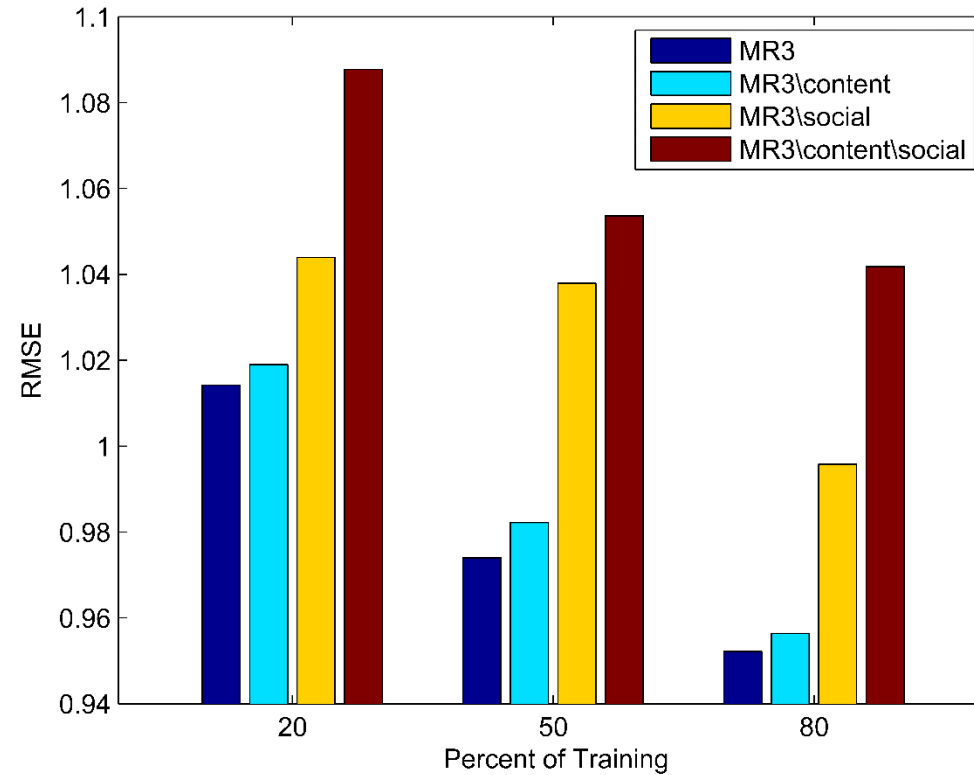
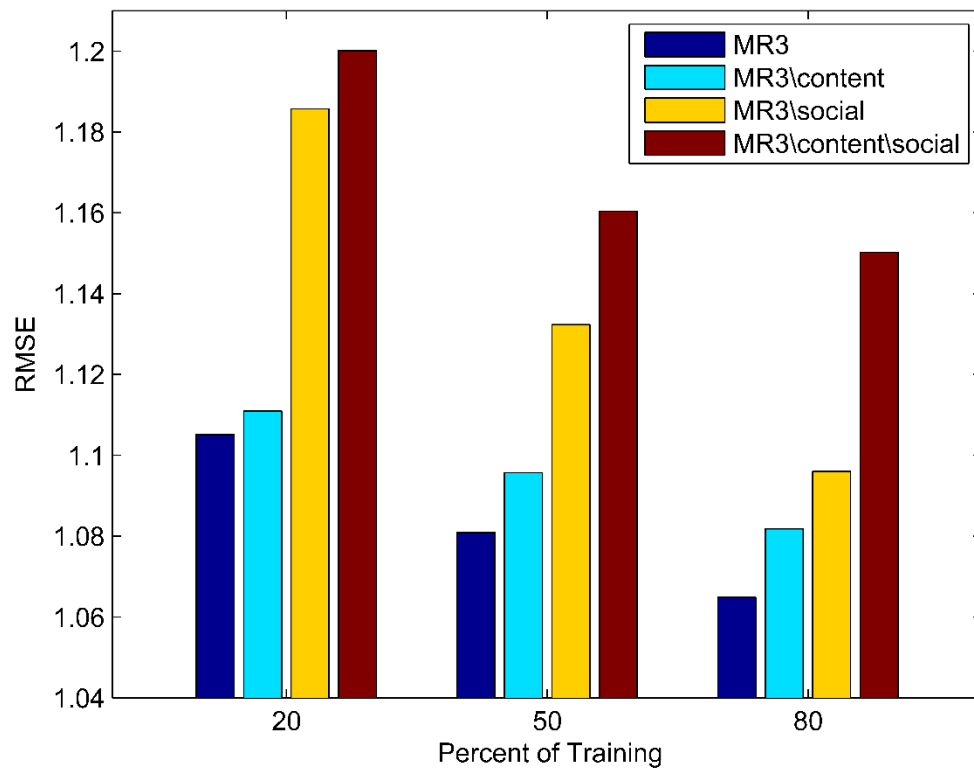
Datasets	Training	Methods				Improvement of MR3 vs.			
		Mean	PMF	HFT	LOCABAL	PMF	HFT	LOCABAL	
Epinions	20%	1.2265	1.2001	1.1857	1.1222	1.1051	8.60%	7.29%	1.55%
	50%	1.2239	1.1604	1.1323	1.1055	1.0809	7.35%	4.76%	2.28%
	80%	1.2225	1.1502	1.0960	1.0892	1.0648	8.02%	2.93%	2.29%
	90%	1.2187	1.1484	1.0867	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 ( $F = 10$ )



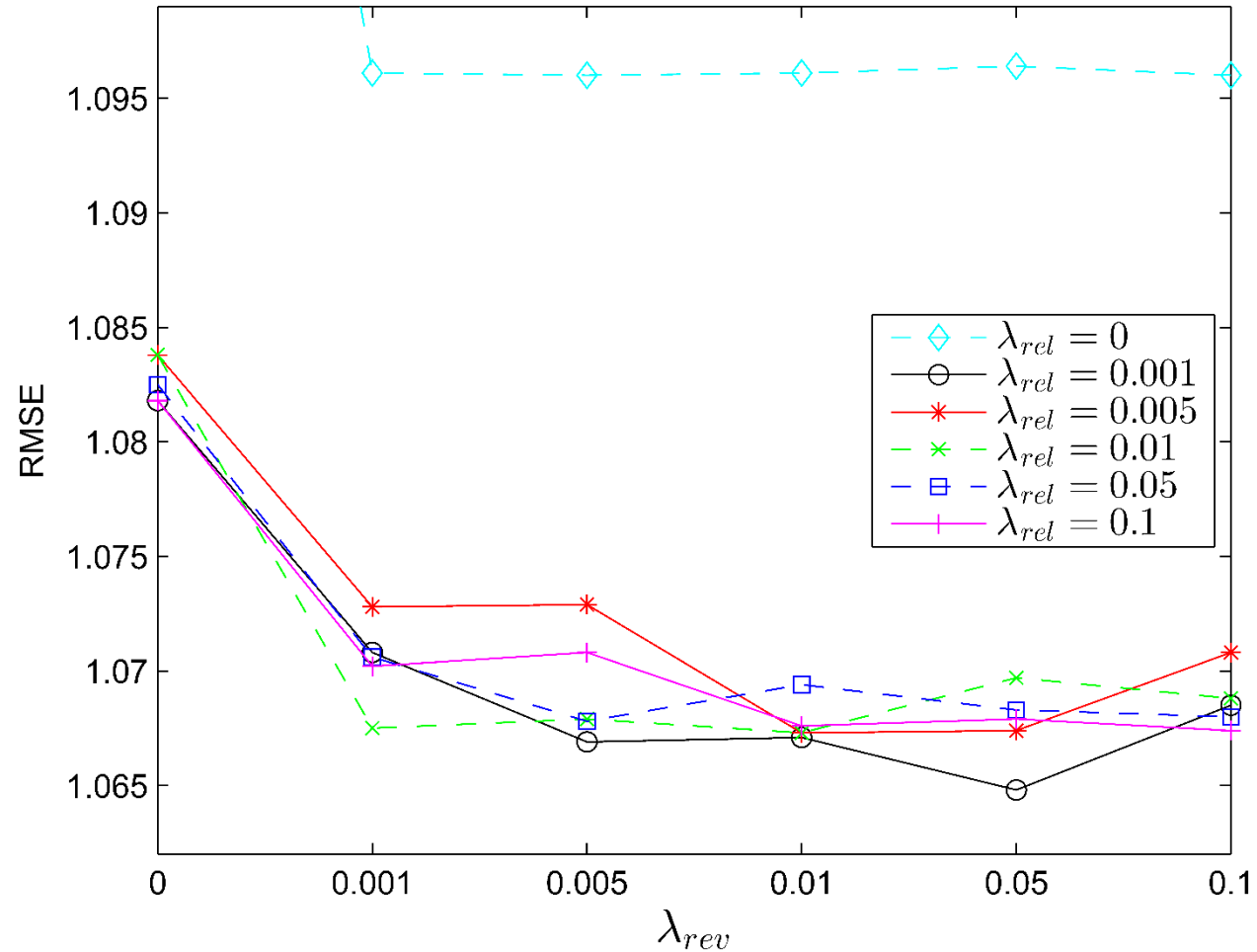
Left: Epinions; Right: Ciao



# Sensitivity to Meta-Parameters



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

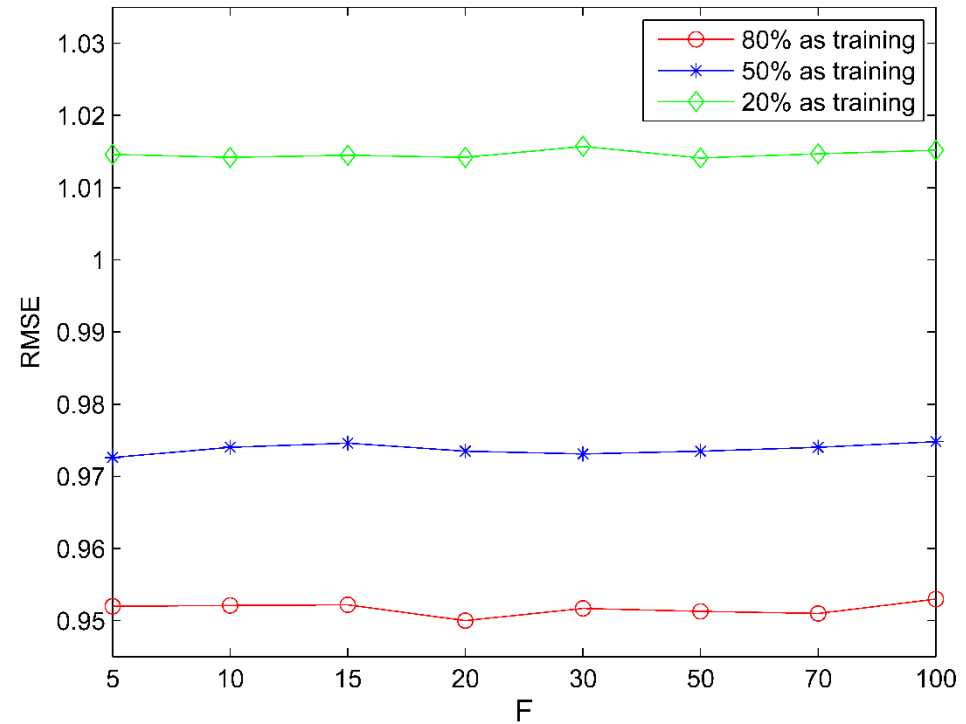
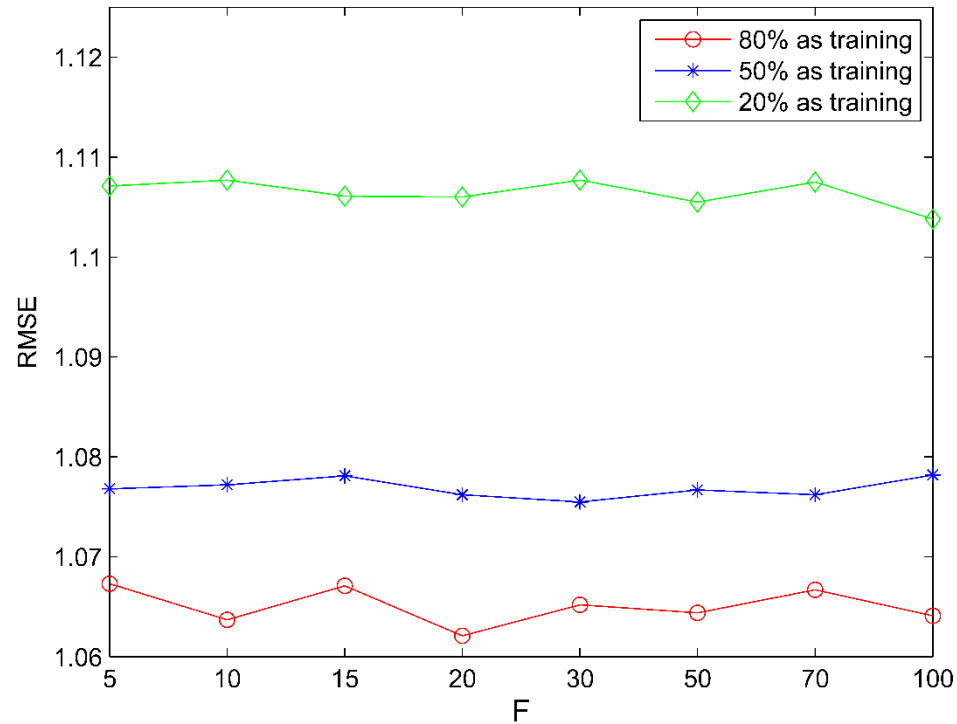




# Sensitivity to Meta-Parameters (cont')



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



Left: Epinions; Right: Ciao



## Part II

An Extension (or the MR3++ model):  
Incorporating Implicit Feedback from Ratings

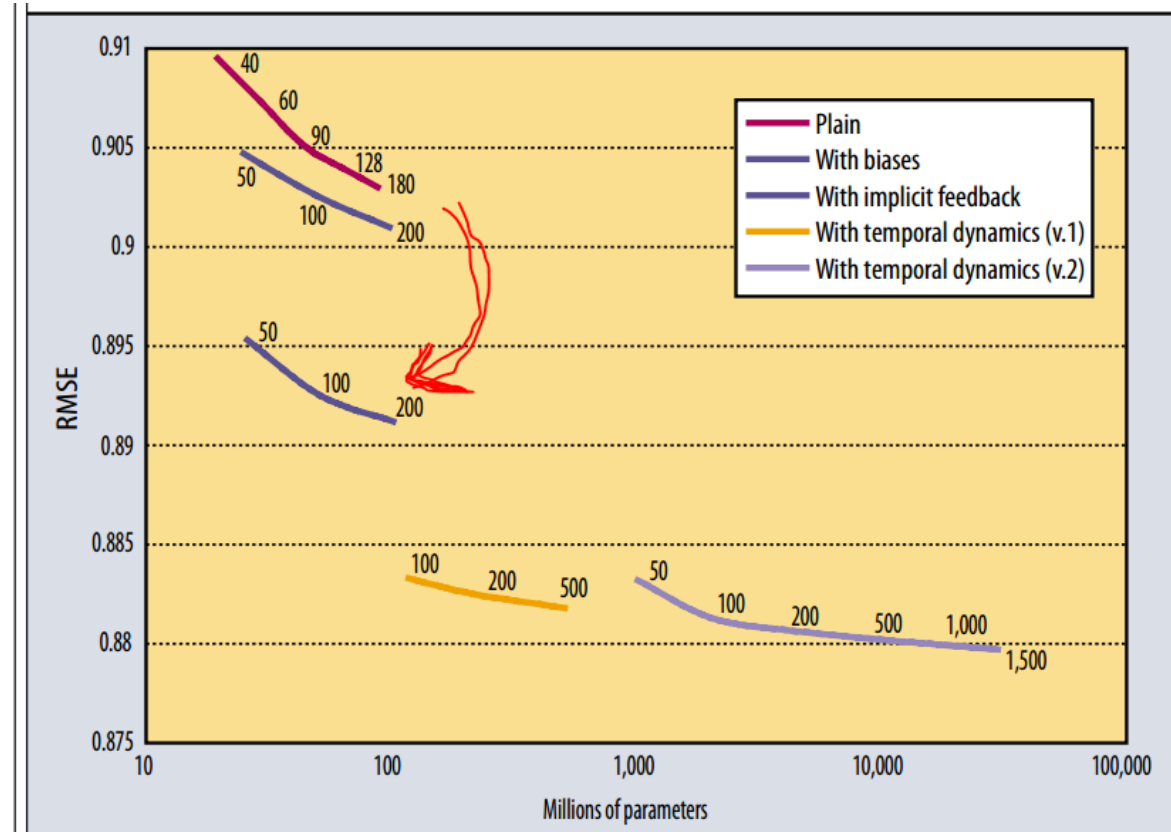




# Why Care about Implicit Feedback?



- Users choose to indicate their preferences implicitly by voting a rating. In another way, users who have rated the similar items are more likely to have similar preferences than those who have not, in an a priori sense.





# Typical Model and Our Extension



- The SVD++ model

$$\hat{R}_{u,i}^* = P_u^T Q_i + \left( |N_u|^{-\frac{1}{2}} \sum_{j \in N_u} Y_j \right)^T Q_i + \mu + b_u + b_i$$

- Our Extension (the MR3++ model)

- Replace the rating component of MR3 by the above model

Y. Koren. Factorization meets the neighborhood: a multifaceted collaborative filtering model. KDD 2008



## Part III

An idea:

Further analysis from the cold-start perspective



# How Helpful of Auxiliary Data Sources?



- We get performance improvement on the whole (e.g., RMSE) when we combine more data sources.
- But ...
  - What's the influence of auxiliary data sources on the cold-start users/items?
  - From the cold-start perspective, what's the relative benefits between integrating more data sources and exploiting the ratings more deep?



# Conclusions



- A framework: exploiting ratings, social relations, and reviews simultaneously for recommendation
- An extension: incorporating implicit feedback from ratings
- An idea: further analysis from the cold-start perspective



# References



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- 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
- Y. Koren. *Factorization meets the neighborhood: a multifaceted collaborative filtering model*. KDD 2008
- Hu et al., *A Synthetic Approach for Recommendation: Combining Ratings, Social Relations, and Reviews*, IJCAI 2015



Thanks  
Q&A

Acknowledgement

