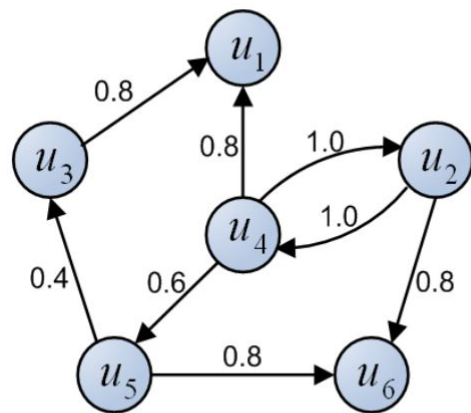


# Trust Aware Recommendation Systems



# Problem



(a) Social Network Graph

	$i_1$	$i_2$	$i_3$	$i_4$	$i_5$	$i_6$	$i_7$	$i_8$
$u_1$	5	2		3		4		
$u_2$	4	3			5			
$u_3$	4		2				2	4
$u_4$								
$u_5$	5	1	2		4	3		
$u_6$	4	3		2	4		3	5

(b) User-Item Matrix

	$i_1$	$i_2$	$i_3$	$i_4$	$i_5$	$i_6$	$i_7$	$i_8$
$u_1$	5	2	2.5	3	4.8	4	2.2	4.8
$u_2$	4	3	2.4	2.9	5	4.1	2.6	4.7
$u_3$	4	1.7	2	3.2	3.9	3.0	2	4
$u_4$	4.8	2.1	2.7	2.6	4.7	3.8	2.4	4.9
$u_5$	5	1	2	3.4	4	3	1.5	4.6
$u_6$	4	3	2.9	2	4	3.4	3	5

(c) Predicted User-Item Matrix

# Regularization Methods : SocialMF

Regularization methods focus on a user's preferences and assume that a user's preferences should be similar to that of her trust network.

# SocialMF

$$\min \sum_{i=1}^n (\mathbf{u}_i - \sum_{u_k \in \mathcal{N}_i} \mathbf{T}_{ik} \mathbf{u}_k)^2,$$

$$\begin{aligned} \min_{\mathbf{U}, \mathbf{V}} & \|\mathbf{W} \odot (\mathbf{R} - \mathbf{U}^\top \mathbf{V})\|_F^2 + \alpha \sum_{i=1}^n (\mathbf{u}_i - \sum_{u_k \in \mathcal{N}_i} \mathbf{T}_{ik} \mathbf{u}_k)^2 \\ & + \lambda (\|\mathbf{U}\|_F^2 + \|\mathbf{V}\|_F^2) \end{aligned}$$

# SocialMF

$$\begin{aligned}\mathcal{L}(R, T, U, V) = & \frac{1}{2} \sum_{u=1}^N \sum_{i=1}^M I_{u,i}^R (R_{u,i} - g(U_u^T V_i))^2 \\ & + \frac{\lambda_U}{2} \sum_{u=1}^N U_u^T U_u + \frac{\lambda_V}{2} \sum_{i=1}^M V_i^T V_i \\ & + \frac{\lambda_T}{2} \sum_{u=1}^N \left( (U_u - \sum_{v \in N_u} T_{u,v} U_v)^T (U_u - \sum_{v \in N_u} T_{u,v} U_v) \right)\end{aligned}$$

# SocialMF

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial U_u} = & \sum_{i=1}^M I_{u,i}^R V_i g'(U_u^T V_i) (g(U_u^T V_i) - R_{u,i}) + \lambda_U U_u \\ & + \lambda_T (U_u - \sum_{v \in N_u} T_{u,v} U_v) - \lambda_T \sum_{\{v | u \in N_v\}} T_{v,u} \left( U_v - \sum_{w \in N_v} T_{v,w} U_w \right) \end{aligned} \quad (13)$$

$$\frac{\partial \mathcal{L}}{\partial V_i} = \sum_{u=1}^N I_{u,i}^R U_u g'(U_u^T V_i) (g(U_u^T V_i) - R_{u,i}) + \lambda_V V_i \quad (14)$$

# Efficiency

Users/Items	Root Mean Square Error	RMSE in paper	Training Data
7000/21000	1.12	1.075	90%
3000/9000	1.078	1.075	90%
7000/21000	1.17	1.075	80%
3000/9000	1.13	1.075	80%

# Regularization Methods: SocialMF

One advantage of these approaches is that they indirectly model the propagation of tastes in social networks, which can be used to mitigate cold-start problem and increase the coverage of items for recommendations.



# Co-factorization Methods

- The underlying assumption of systems in this group is that the  $i$ -th user  $u_i$  should share the same user preference vector  $u_i$  in the rating space (rating information) and the trust relation space.
- Systems in this group perform a co-factorization in the user-item matrix and the user-user trust relation matrix by sharing the same user preference latent factor.

# Sorec

$$\min \sum_{i=1}^n \sum_{u_k \in \mathcal{F}_i} (S_{ik} - \mathbf{U}_i^\top \mathbf{Z}_k)^2,$$

$$\begin{aligned} \min_{\mathbf{U}, \mathbf{V}, \mathbf{Z}} & \|\mathbf{W} \odot (\mathbf{R} - \mathbf{U}^\top \mathbf{V})\|_F^2 + \alpha \sum_{i=1}^n \sum_{u_k \in \mathcal{F}_i} (S_{ik} - \mathbf{U}_i^\top \mathbf{Z}_k)^2 \\ & + \lambda (\|\mathbf{U}\|_F^2 + \|\mathbf{V}\|_F^2 + \|\mathbf{Z}\|_F^2), \end{aligned}$$

# Hybrid: Sorec and SocialMF

- The  $i$ -th user  $u_i$  should share the same user preference vector  $u_i$  in the rating space (rating information) and the trust relation space.
- A user's preferences should be similar to that of his trust network.

# Sorec

$$\min \sum_{i=1}^n \sum_{\mathbf{u}_k \in \mathcal{F}_i} (\mathbf{S}_{ik} - \mathbf{U}_i^\top \mathbf{Z}_k)^2,$$

$$\min \sum_{i=1}^n (\mathbf{u}_i - \sum_{\mathbf{u}_k \in \mathcal{N}_i} \mathbf{T}_{ik} \mathbf{u}_k)^2,$$

# Has Potential

- 90% Train, 10% Test, 3000 Users, 9000 items.

SocialMF : 1.078 RMSE

Hybrid : 1.054 RMSE

- This was the least error across multiple runs.

# Zomato

- Very few datasets with trust relations and item ratings.
- Most just use opinions, some papers introduce new ones with slightly different density.
- Api exists but only for restaurants and their ratings.
- Idea was to use “followers” as one way trust relation.

# Zomato: Challenges

- Default scraping didn't work.
- User agent spoofing, but got static web pages.
- Selenium worked but very slow.
- Had to find post URL and use it for scraping.

# Zomato: Comparison with Epinions

Parameters\Datasets	Epinions	Zomato
Users	49,290	8028
Items	1,39,738	92,324
Items Ratings	6,64,823	2,33,974
Trust Relations	4,87,182	38,84,886



# More Trust, Lesser Error

- 90% Train, 10% Test, 3000 Users, 9000 items. Sorec.

Epinions : 0.87 MAE

Zomato : 0.53 MAE

# Overview

- Identified core ideas/papers in Trust Based Recommendation Systems and implemented and compared them to know advantages and disadvantages of each.
- Tried to leverage previous understanding to create a hybrid approach and improve performance.
- Contributions: Created a new dataset with high trust density.

# Thanks!

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