Implicit vs. Explicit trust in Social Matrix Factorization

Soude Fazeli, Babak Loni, Alejandro Bellogín, Hendrik Drachsler, Peter Sloep

{soude.fazeli, hendrik.drachsler,peter.sloep}@ou.nl; alejandro.bellogin@uam.es;
b.loni@tudelft.nl

Motivation

- Incorporating social trust in Matrix Factorization (MF) proved to improve rating prediction accuracy
- Such approaches assume that users themselves explicitly express the trust scores.
- It is often very challenging to have users giving trust scores of each other but implicit trust scores may be predicted based on the users' interaction histories.
- Problem: how to compute and predict trust between users more accurately and effectively.

Contribution

1. We evaluate several well-known Trust Metrics (TM) to find out which one is closest to the real, explicit scores, and therefore, can make the most accurate trust prediction.
2. We try to incorporate the candidate TMs in social MF to answer this research question: Can we incorporate implicit trust into social matrix factorization when explicit trust relations are not available?

Empirical study

Dataset: Epinions

Number of user: 49,290

Number of items: 139,738

Issued trust statements: 487,181

Trust metric	Computation function
O'Donovan & Smyth (TM1) [9]	$t_{u,v} = \frac{\lvert CorrectSet(v)\rvert}{\lvert RecSet(v)\rvert}$ $correct(r_{u,i}, r_{v,i)} \leftrightarrow \lvert p_{u,i} - r_{u,i}\rvert$
Lathia et al. (TM2) [7]	$t_{u,v} = \frac{1}{\lvert I_{u,v}\rvert} \sum_{i \in I_{u,v}} (1 - \frac{\lvert r_{u,i} - r_{v,i)}\rvert}{r_{max}})$
Hwang & Chen (TM3) [4]	$t_{u,v} = \frac{1}{\lvert I_{u,v}\rvert} \sum_{i \in I_{u,v}} (1 - \frac{\lvert p_{u,i} - r_{u,i)}\rvert}{r_{max}})$ $p_{u,i} = r_u + (\bar{r}_{v,i} - \bar{r}_v)$
Shambour & Lu (TM4) [12]	$t_{u,v} = \frac{\lvert I_{u,v}\rvert}{\lvert I_u \cup I_v\rvert}(1 - \frac{1}{\lvert I_{u,v}\rvert} \sum_{i \in I_{u,v}} \left(\frac{p_{u,i} - r_{u,i}}{r_{max}}\right)^2)$ $p_{u,i} = r_u + (\bar{r}_{v,i} - \bar{r}_v)$
Papagelis et al. (TM5) [10]	$t_{u,v} = \begin{cases} s_{u,v}, if\ s_{u,v} > \theta_s, \lvert I_{u,v}\rvert > \theta_I \\ 0, \quad otherwise; \end{cases}$ $s_{u,v} = \frac{\sum_i(\bar{r}_{u,i} - \bar{r}_u)(\bar{r}_{v,i} - \bar{r}_v)}{\sqrt{\sum_i(\bar{r}_{u,i} - \bar{r}_u)^2}\sqrt{\sum_i(\bar{r}_{v,i} - \bar{r}_v)^2}}$

Comparing the inferred trust scores (implicit) with the ground trust scores (explicit)

Trust metric	nDCG@10	nDCG	P@10	R@10	MRR	Cvg
O'Donovan & Smyth [9] (TM1)	0.007	0.008	0.007	0.001	0.022	98.8%
Lathia et al. [7] (TM2)	0.004	0.008	0.004	0.001	0.014	99.7%
Hwang & Chen [4] (TM3)	0.006	0.009	0.005	0.001	0.020	100%
Shambour & Lu [12] (TM4)	0.006	0.009	0.005	0.001	0.017	100%
Papagelis et al. [10] (TM5)	0.028	0.007	0.024	0.003	0.071	9.5%

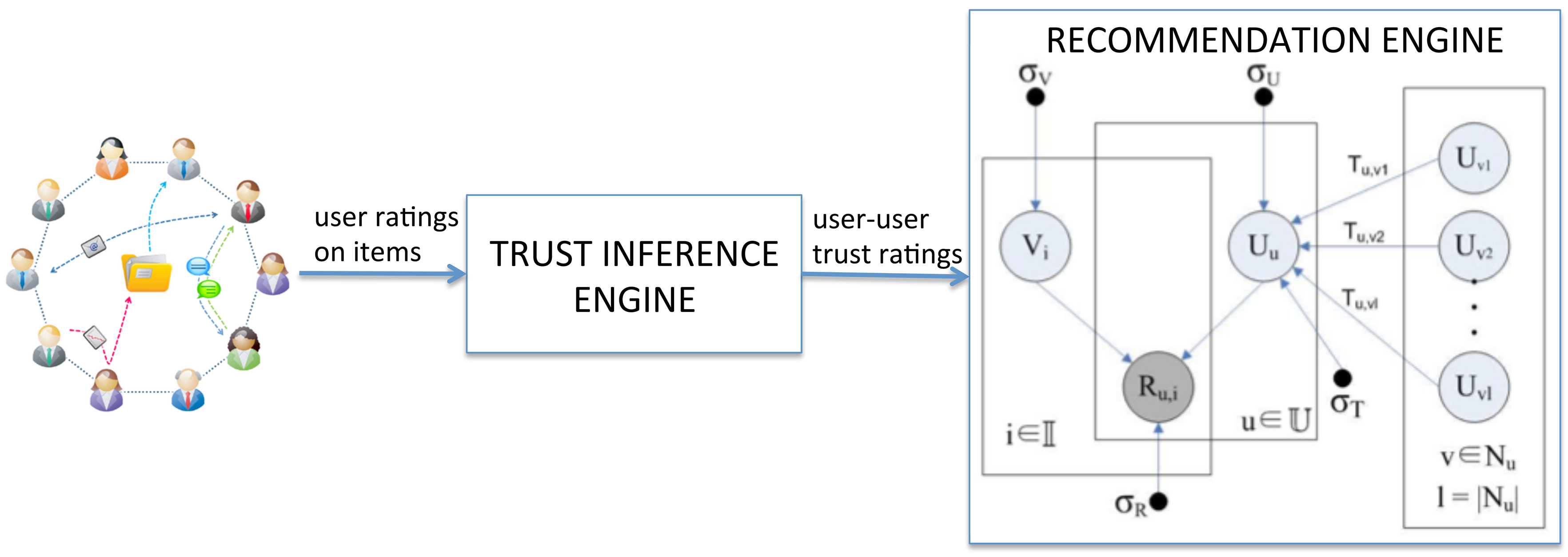
Performance comparison of the SocialMF using implicit trust against the baselines (the lower, the better); lowest values for each k in bold face and best values underlined.

	RMSE		MAE	
Method/k	k=5	k=10	k=5	k=10
PMF	1.1741	1.1705	0.9471	0.9507
SocialMF-explicit trust	1.0956	**1.0934**	0.9161	**0.9154**
SocialMF-TM1: O'Donovan & Smyth [9]	<u>**1.0926**</u>	1.1003	<u>**0.9145**</u>	0.9170
SocialMF-TM2: Lathia et al. [7]	1.0968	1.1005	0.9160	0.9175
SocialMF-TM3: Hwang & Chen [4]	1.0947	1.1006	0.9154	0.9174
SocialMF-TM4: Shambour & Lu [12]	1.0952	1.0990	0.9153	0.9167
SocialMF-TM5: Papagelis et al. [10]	1.0970	1.1065	0.9150	0.9186

Discussion

- The metric defined by O'Donovan and Smyth performs best although there is a trade-off between accuracy and coverage.
- The SocialMF on implicit trust inferred by O'Donovan and Smyth's (TM1) can perform as accurate as the SocialMF with explicit trust.
- The implicit trust can be incorporated into the social matrix factorization whenever explicit trust is not available.
- The results of prediction accuracy (MAE and RMSE) conform to the results of comparing the trust metrics where O'Donovan and Smyth's (TM1) was selected as the best candidate for inferring trust scores.

Proposed approach



Conclusions

The social MF with implicit trust outperforms one of the baselines (PMF) and performs in ways similar to the SocialMF using explicit trust.

A clear advantage of this result is that, since we often have no trust scores explicitly given by users in social networks, we can overcome this problem by using implicit (or inferred) trust scores and incorporate them into the recommender.

Future Work

In the future, we aim to define and infer trust scores taking into account context data of users rather than their ratings only.

We also want to evaluate additional dimensions of recommendation quality, such as diversity, novelty or serendipity.

References

Guo, G., Zhang, J., Thalmann, D., Basu, A. and Yorke-smith, N. 2014. From Ratings to Trust : an Empirical Study of Implicit Trust in Recommender Systems. Symposium on Applied Computing - Recommender Systems 2014 (2014).

Jamali, M. and Ester, M. 2010. A Matrix Factorization Technique with Trust Propagation for Recommendation in Social Networks Categories and Subject Descriptors. Proceedings of the fourth ACM conference on Recommender systems (2010), 135–142.

Koren, Y., Bell, R. and Volinsky, C. 2009. Matrix factorization techniques for recommender systems. IEEE Computer. (2009), 30–37.

O'Donovan, J. and Smyth, B. 2005. Trust in recommender systems. Proceedings of the 10th international conference on Intelligent user interfaces (2005), 167–174.

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