

Implicit vs. Explicit Trust in Social Matrix Factorization

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ABSTRACT

Incorporating social trust in Matrix Factorization (MF) methods demonstrably improves accuracy of rating prediction. Such approaches mainly use the trust scores explicitly expressed by users. However, it is often challenging to have users provide explicit trust scores of each other. There exist quite a few works, which propose Trust Metrics (TM) to compute and predict trust scores between users based on their interactions. In this paper, we first evaluate several TMs to find out which one can best predict trust scores compared to the actual trust scores explicitly expressed by users. And, second, we propose to incorporate these trust scores inferred from the candidate TMs into social matrix factorization (MF). We investigate if incorporating the implicit trust scores in MF can make rating prediction as accurate as the MF on explicit trust scores. The reported results support the idea of employing implicit trust into MF whenever explicit trust is not available, since the performance of both models is similar.

Categories and Subject Descriptors

H.3.3 [Information Search and Retrieval]: Information filtering

General Terms

Algorithms, Performance, Experimentation

Keywords

recommender system, matrix factorization, implicit trust, social network, rating, similarity

1. INTRODUCTION

Quite a few works discuss incorporating social trust in Matrix Factorization (MF), which proved to improve rating prediction

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accuracy [5, 8]. Such approaches assume that users themselves explicitly express the trust scores. Examples of well-known and publicly available datasets are Epinions and FilmTrust. However, there are still certain issues with this kind of trust scores. First, it is often very challenging to have users giving trust scores of each other. Second, even these publicly available datasets for trust only provide trust relations in binary format (0/1), usually, and as stated in the literature, because of privacy concerns. Therefore, trust relations will all be considered equal and we will ignore the fact that users can have different levels of trust of each other.

In contrast, implicit trust scores may be predicted based on the users' interaction histories. This is also true in the context of real life scenarios. People often tend to share and interact with people they trust. Nevertheless, it is still an open problem how to compute and predict trust between users more accurately and effectively. In this paper:

First, 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.

Second, we try to incorporate the candidate TMs in the MF to answer this research question: *Can we incorporate implicit trust into social matrix factorization when explicit trust relations are not available?*

The rest of the article is organized as follows: Section 2 presents a brief review of the existing TMs. Section 3 provides the problem definition for MF. Our proposed approach is presented in Section 4. Section 5 presents the results and discussions. Finally, we conclude by giving an overview of further work in Section 5.

2. FROM RATINGS TO TRUST

Trust is known to be a complex and ambiguous concept in various domains. However, in recommender systems it is a fairly simple and precise notion: it is correlated with similarity of interests and preferences of users sharing the same items. Guo [2] presents this definition for trust in recommender systems: "Trust is defined as one's belief towards the ability of others in providing valuable ratings". In general, trust has a number of distinct properties [3]:

- Asymmetry. Trust is personal and subjective. People might have different opinions about a particular person based on their background and experiences with that

person. If user Alice trusts Bob, Bob does not necessarily trust Alice.

- **Transitivity.** A very useful property of trust in recommender systems is transitivity; by and large, it holds in real life scenarios as well. People tend to trust friends of a friend more so than strangers. So, if Alice trusts Bob, and Bob trusts Carol, Alice is likely to trust Carol too. This property helps to identify new neighbors (likeminded users) for a target user by propagating trust in social networks and thus, to improve performance of recommender systems.
- **Dynamicity.** Trust between two persons often gradually develops and changes over time. In recommender systems, trust grows over time as two users share more opinions on common items.
- **Context dependence.** Trust can depend strongly on the context in which it has formed. The context in recommender systems can refer to the type of the items users give ratings to or to other specific properties in the user or item profile.

Table 1. Trust prediction metrics

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

Table 1 presents several trust metrics that compute trust scores between users based on their rating data. For all trust metrics in this table, U , I , and R are sets of users, items, and ratings, respectively. The trust values between two users u and v ($t_{u,v}$) are inferred based on their co-rated items ($I_{u,v}$). We use $p_{u,i}$ as the predicted rating value for a user u on an item i . The average of ratings for user u is denoted by \bar{r}_u for all the items rated by user u . Finally, r_{max} is the maximum value of ratings.

As for O'Donovan & Smyth [9] (TM1 in Table 1), the $CorrectSet(v)$ is the set of correct ratings given by the user v , and $RecSet(v)$ is the whole set of recommendations made for user v . Moreover, in the trust metric proposed by Papagelis et al. [10] (TM5 in Table 1), the similarity threshold (θ_s) is set to ensure that the inferred trust is transitive only when the two users v and u are highly correlated. Moreover, when the number of co-rated items

between the users v and u is too small, there might be a risk that the inferred trust value is less reliable. Hence, Papagelis et al. [10] sets a threshold (θ_l) to address this as well.

As indicated, we will first evaluate the trust metrics in Table 1 by comparing the trust scores generated by them with the grounded trust scores explicitly expressed by users. We do this to find out which of these trust metrics can best predict the trust scores between users. The trust metrics presented in Table 1 are all based on differences between a user's ratings and its neighbors' ratings. Therefore, for all of them, similarity is an emergent property of the trust relationship and not necessarily the cause of it. So, they all are asymmetric and transitive. However, none of them provides dynamicity and context-dependence.

3. SOCIAL MATRIX FACTORIZATION

In recommender systems, we have a set of users $\{u_1, \dots, u_N\}$ and set of items $\{i_1, \dots, i_M\}$. The rating matrix $R = [R_{u,i}]_{N \times M}$ provide the ratings given by users to items. Therefore, $R_{u,i}$ is the rating of user u to item i . The ratings are often on a five-star scale. The recommender system's task is then to predict the rating a user u would give to an item i whenever $R_{u,i}$ is unknown. In this paper, we follow the basic idea of the social matrix factorization (SocialMF) method [5] to learn the latent features of both users and items more precisely when trust information between users is available. Let us assume $U \in R_{K \times N}$ and $V \in R_{K \times M}$ be latent user and item feature matrices, with column vectors U_u and V_i representing K -dimensional user-specific and item-specific latent feature vectors of users u and item i , respectively. The goal of matrix factorization is to learn these latent features and, subsequently, to employ them for making rating predictions [6].

Now assume that $T_{u,v}$ denotes the trust value between users u and v . Therefore, matrix $T = [T_{u,v}]_{N \times N}$ represent all trust scores between users. Note that T is asymmetric in general. The SocialMF model [5] exploits these trust scores to learn the latent features more precisely. As the trust scores are incorporated into SocialMF, the loss function is defined as follows [5]:

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

Where $g(\cdot)$ is a logistic normalization function and $\lambda_U, \lambda_V, \lambda_T$ are biases for user, item and trust, respectively. The model learns the latent features using a gradient descent method.

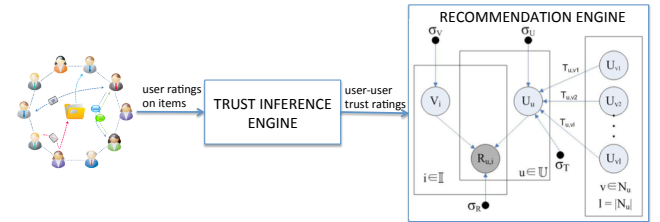


Figure 1. Our proposed approach based on the SocialMF model

4. A TRUST-AWARE SOCIAL MF

As mentioned before, each of the trust-aware recommenders and the social MF alone proved to improve accuracy of ratings prediction. In this paper, we propose to incorporate implicit trust scores between users in the social MF in order to boost

performance of model-based recommender systems. Figure 1 shows how we want to combine inferred trust scores based on user ratings on items, with the social MF. As shown in Figure 1, the approach we propose consists of two main modules: a trust inference engine and a recommendation engine. The trust inference engine takes user ratings on items as input and computes the trust scores between users using any of the trust metrics in the literature (such as those presented in Table 1). Then, the recommendation engine generates rating predictions by employing the SocialMF method [5], using the inferred trust scores instead of the explicit ones.

5. EXPERIMENT

We used the Epinions¹ dataset, which includes 49,290 users who rated a total of 139,738 different items, 664,824 reviews, and 487,181 issued trust statements. Our experiment consists of two steps. First, we evaluate the trust metrics in Table 1, by comparing the trust scores generated by them with the ground trust scores explicitly expressed by users (Table 2). Second, we incorporate the trust scores generated by the trust metrics, into the SocialMF as described in the previous section (Table 3).

5.1 Evaluating trust ratings predictions

Here, we present results of an evaluation of the trust metrics presented in Section 2. For each metric, we have measured how relevant a user’s ranking (composed of other users, and sorted according to the trust scores produced by the metrics) is, compared against the ground truth scores available in Epinions dataset. Specifically, four metrics commonly used in Information Retrieval are presented: normalized discounted cumulative gain (nDCG), precision (P), recall (R), and reciprocal rank (MRR) [1]. Table 2 shows the results for these metrics; along with the user coverage (Cvg) measured as the number of users for which a metric is able to infer trust values.

Table 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%

As Table 2 shows, there is an important tradeoff between accuracy and coverage: whereas Papagelis et al. (TM5) has high precision and MRR values, its coverage is too low. It is also important to note the difference in performance at varying cutoffs: although Papagelis et al. perform well at smaller cutoffs (nDCG@10), its performance is worse when the whole ranking is considered (nDCG); in particular, this metric is not the best performing one, but more complex metrics like Hwang & Chen

(TM3) and Shambour & Lu (TM4) obtain better performance in the long term.

Assuming we are interested in metrics with high user coverage and good performance at small cutoffs, our results suggest O’Donovan and Smyth (TM1) is the best candidate. This is due to a good tradeoff this metric presents between the different aspects measured over the trust metrics from Table 1.

5.2 Evaluating accuracy of ratings prediction

In this section, we present results on accuracy of rating prediction in terms of RMSE (Root Mean Square Error) and MAE (Mean Absolute Error), which are common metrics used when evaluating MF methods. We set the number of latent features k to be equal to 5 and 10; as suggested in the literature on social MF [5, 8]. For testing our model, 80% of the data was randomly selected and assigned to training set and the rest was considered as test set. We compare our approach with two state-of-the-art approaches: Probabilistic MF (PMF) [11] and an approach using only trust information, SocialMF [5]. For all the methods used, we set optimal parameters recommended in the literature, as indicated in Table 3. For PMF and SocialMF, we adopt the implementations provided by the MyMediaLite framework².

Table 3. 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.

Method/ k	RMSE		MAE	
	$k=5$	$k=10$	$k=5$	$k=10$
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

Table 3 presents the results of comparing the SocialMF on implicit trust scores, explicit trust scores, and PMF. Based on the results, all SocialMFs that incorporates implicit trust outperforms the PMF; the largest difference is 8.2% and smallest difference is 7.7%.

In general, the results of SocialMF on implicit trust (for all TMs) are quite similar to the results of SocialMF using explicit trust. As the table shows, the SocialMF on implicit trust inferred by O’Donovan and Smyth’s (TM1) (RMSE=1.0926; MAE=0.9145) can perform as accurate as the SocialMF with explicit trust (1.0956; $k=5$). The results show that SocialMF on implicit trust can achieve quite the same results as the SocialMF on explicit trust; with the difference in range of $\{-0.016\%, +0.4\%\}$. Regarding

¹ http://www.trustlet.org/wiki/Epinions_dataset

² www.mymedialite.net

our research question in Section 1, we may safely conclude that the implicit trust can be incorporated into the social matrix factorization whenever explicit trust is not available. Moreover, the results in Table 3 conform to the results presented in the previous section (Table 2) where TM1 was selected as the best candidate for inferring trust scores.

5.3 Impact of social regulation (λ_T) on results

As described in Section 3, our model has a parameter λ_T that indicates the impact of social trust scores in the trust learning process. To analyze how sensitive our model is to this parameter, Figure 2 shows the effect of changing the value of λ_T in the range of $[0, 3]$, specifically, we show the RMSE of the SocialMF model for different values of this parameter. As shown in this figure, $\lambda_T = 1$ seems to be a good candidate for our experiment since the SocialMF model provides the lowest RMSE at this value.

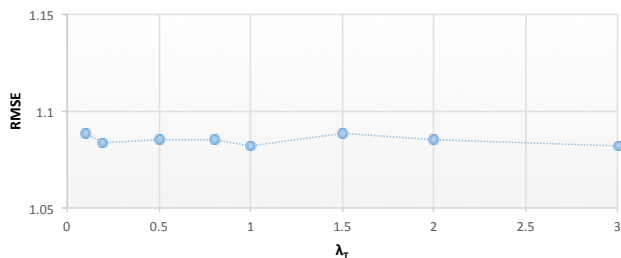


Figure 2. Effect of changes in social regulations on the RMSE

6. CONCLUSION AND FUTURE WORK

In this paper, we addressed the following research question: *Can we incorporate implicit trust into social matrix factorization when explicit trust relations are not available?* For this, we have investigated which trust metric can provide us with the most accurate trust scores in comparison with the explicit trust scores given by users themselves. Our results show that there is a trade-off between accuracy and coverage, but that the metric defined by O'Donovan and Smyth in [9] performs best. Then, we incorporated these inferred trust scores into a social matrix factorization recommender. The results show that 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. 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.

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8. REFERENCES

- [1] Baeza-Yates, R.A. and Ribeiro-Neto, B.A. 2011. *Modern Information Retrieval - the concepts and technology behind search, Second edition*. Pearson Education Ltd., Harlow, England.
- [2] Guo, G. 2013. Integrating trust and similarity to ameliorate the data sparsity and cold start for recommender systems. *In Proceedings of the 7th ACM Conference on Recommender Systems (RecSys) (2013)*.
- [3] 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)*.
- [4] Hwang, C.-S. and Chen, Y.-P. 2007. Using trust in collaborative filtering recommendation. *In New Trends in Applied Artificial Intelligence (2007)*.
- [5] 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.
- [6] Koren, Y., Bell, R. and Volinsky, C. 2009. Matrix factorization techniques for recommender systems. *IEEE Computer (2009)*, 30–37.
- [7] Lathia, N., Hailes, S. and Capra, L. 2008. Trust-Based Collaborative Filtering. *Trust Management II, IFIP Advances in Information and Communication Technology*. 263/2008, (2008).
- [8] Ma, H., Yang, H., Lyu, M.R. and King, I. 2008. SoRec. *Proceeding of the 17th ACM conference on Information and knowledge mining - CIKM '08 (New York, New York, USA, Oct. 2008)*, 931.
- [9] O'Donovan, J. and Smyth, B. 2005. Trust in recommender systems. *Proceedings of the 10th international conference on Intelligent user interfaces (2005)*, 167–174.
- [10] Papagelis, M., Plexousakis, D. and Kutsuras, T. 2005. Alleviating the sparsity problem of collaborative filtering using trust inferences. *In Trust management (2005)*.
- [11] Salakhutdinov, R. and Mnih, A. Probabilistic matrix factorization. *In NIPS 2008*. 20.
- [12] Shambour, Q. and Lu, A, J. 2012. Trust-semantic fusion-based recommendation approach for e-business applications. *Decision Support Systems*. 54 (2012), 768–780.