Learning to Recommend with Multi-Faceted Trust in Social Networks

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ABSTRACT

Traditionally, trust-aware recommendation methods that utilize trust relations for recommender systems assume a single type of trust between users. However, this assumption ignores the fact that trust as a social concept inherently has many aspects. A user may place trust differently to different people. Motivated by this observation, we propose a novel probabilistic factor analysis method, which learns the multi-faceted trust relations and user profiles through a shared user latent feature space. Experimental results on the real product rating data set show that our approach outperforms state-of-the-art methods on the $RMSE$ measure.

Categories and Subject Descriptors

H.3.3 [**Information Systems**]: Information Filtering; J.4 [**Computer Applications**]: Social and Behavioral Sciences

Keywords

Probabilistic Matrix Factorization, Multi-Faceted Trust, Social Recommendation

1. INTRODUCTION

Recently, several trust-aware recommendation methods have been proposed to improve the performance of traditional recommender systems[1][2]. Most of them assume that two trusted friends will have similar tastes, and the mutual trust relationships are single and homogeneous.

However, trust as a social concept is intrinsically multi-faceted and heterogenous[3][4]. Intuitively, a user may trust different people in different domains. For example, in multi-category recommender systems, a user may trust an expert in Movies category while not trust him/her in Cars category. Treat trust relationships of different categories equally will not capture the multi-faceted features hidden below the surface.

To solve above problem, we propose to fuse the users' category information with the rating matrix using a probabilistic matrix factorization method named mTrustMF. We model multi-faceted trust and users' tastes through a shared user latent feature space, i.e., the user latent feature space in user categories is the same in the rating matrix. Experimental results show that our approach outperforms state-of-the-art algorithms in terms of $RMSE$.

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2. RECOMMENDATION FRAMEWORK

In this section, we first introduce the classic trust-aware recommendation method SocialMF[1], and then focus on how to model multi-faceted trust relation as a regularization term to constrain an extended matrix factorization framework.

Suppose we have a $m \times n$ rating matrix $R = \{r_{ij}\}$ denoting m users' numerical ratings on n multi-category items. Users can also maintain a trust list, which presents a network $S = \{s_{it}\}$ of trust relationships between users. Trust-aware recommender systems assume that users would always turn to their friends for recommendation since they trust them. For example, SocialMF method tries to derive a high-quality l-dimensional feature representation U of users by employing the tastes of their trusted friends $t \in N_i$. Let $U \in \mathbb{R}^{l\times m}$ and $V \in \mathbb{R}^{l\times n}$ be the inferred latent user and item feature matrices, with column vectors U_i and V_j representing user-specific and item-specific feature vectors, respectively. The objective function of SocialMF can be given by:

$$\begin{aligned} E(R,S,U,V) &= \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}^{R}(r_{ij} - g(U_i^T V_j))^2 \\ &+ \frac{\lambda_S}{2}\sum_{i=1}^{m}(U_i - \sum_{t\in N_i} s_{it}U_t)^T (U_i - \sum_{t\in N_i} s_{it}U_t) \\ &+ \frac{\lambda_U}{2}\|U\|_F^2 + \frac{\lambda_V}{2}\|V\|_F^2, \end{aligned} \tag{1}$$

where $\lambda_S, \lambda_U, \lambda_V > 0$, I_{ij}^R is the indicator function that is equal to 1 if user u_i rated item v_j; 0 otherwise. $g(x)$ is the logistic function $g(x) = 1/(1 + exp(-x))$, $\|\cdot\|_F^2$ denotes the Frobenius norm.

The above function makes an assumption that trust relations of different categories have the same influence to the target users. However, as mentioned in Section 1, trust is multi-faceted. In order to reflect the fact that a user's multi-faceted trust relations will affect his/her decisions on items, we connect user-category and user-item rating matrix through a shared user latent feature space. The objective function is defined as:

$$\begin{aligned} E(R,S,C,U,V,W) &= \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}^{R}(r_{ij} - g(U_i^T V_j))^2 \\ &+ \frac{\lambda_C}{2}\sum_{i=1}^{m}\sum_{k=1}^{m} I_{ik}^{C}(c_{ik} - g(U_i^T W_k))^2 \\ &+ \frac{\lambda_S}{2}\sum_{i=1}^{m}(U_i - \sum_{t\in N_i} s_{it}U_t)^T (U_i - \sum_{t\in N_i} s_{it}U_t) \end{aligned}$$

$$+\frac{\lambda_U}{2}\|U\|_F^2+\frac{\lambda_V}{2}\|V\|_F^2+\frac{\lambda_W}{2}\|W\|_F^2, \quad (2)$$

where $\lambda_C, \lambda_W > 0$. $C = \{c_{ij}\}$ is the user-category matrix, which can be derived from the categories of users' interested items. W is the derived latent category factors. I_{ik}^C is the indicator function that is equal to 1 if user u_i belongs to category c_k; 0 otherwise.

In the above objective function, we impose a category regularization term

$$\frac{\lambda_C}{2}\sum_{i=1}^{m}\sum_{k=1}^{m} I_{ik}^C(c_{ik}-g(U_i^T W_k))^2 \quad (3)$$

to constrain users' feature vectors. More specifically, user u_i's latent feature vectors should be close to the average of the latent feature vectors of his trusted friends in the same categories with u_i.

A local minimum of the objective function given by Eq.2 can be found by performing gradient descent in U, V and W.

3. EXPERIMENTAL ANALYSIS

In this section, we conduct several experiments to compare our approach with two state-of-the-art recommendation methods.

3.1 Dataset and Metric

We use Epinions[4] as the data source of our recommendation method, which consists of 22,166 users who have rated 296,277 items in 27 different categories. The total number of issued trust statements and ratings is 355,813 and 922,267, respectively. In experiments, we choose the commonly used Root Mean Square Error ($RMSE$)[5] metric to measure the recommendation performance, where lower $RMSE$ means better performance.

Table 1: Performance Comparisons

Method	PMF	SocialMF	mTrustMF
K=5	1.02869	1.02691	**1.02590**
K=10	1.02870	1.02692	**1.02581**

3.2 Comparisons

To evaluate the performance of our mTrustMF approach, we compare our method with two popular methods: PMF[6] and SocialMF.

Table 1 presents the experimental results on the Epinions data set with different settings of dimensionality K. The parameter settings of our method are $\lambda_C = 10$, $\lambda_S = 5$, $\lambda_U = \lambda_V = \lambda_W = 30$. From Table 1, we can observe that the basic PMF method performs worse than the other two trust-aware recommendation algorithms, which indicates that purely utilizing users' preference histories is not suitable. Note that, our mTrustMF approach achieves better performance than SocialMF, which demonstrates that simply treating trust relations equally will not generate satisfactory results, and it is beneficial to learn user features from multi-faceted trust relations.

3.3 Impact of Parameter λ_C

In our method, parameter λ_C controls how much our mTrustMF approach depends on the user-category matrix.

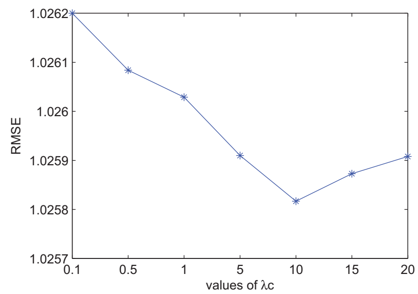

Figure 1: Impact of Parameter λ_C (K=10)

If $\lambda_C = 0$, we will simply treat trust relations single and homogeneous for recommendation, and if $\lambda_C \to \infty$, we will only derive latent user feature vectors over categories. In other cases, we fuse information from trust network, user-category and user-item rating matrix for recommendation.

Fig.1 illustrates how the changes of λ_C affect the prediction accuracy. We notice that the value of λ_C affects the recommendation results significantly, which indicates that incorporating the user-category matrix considerably improves the prediction accuracy. As λ_C increases, the value of $RMSE$ decreases (prediction accuracy increases) at first, but when λ_C surpasses a certain threshold, the $RMSE$ increases (prediction accuracy decreases) with further increase of the value of λ_C. From this experiment result, we observe that purely taking trust relations at face value or purely using the user-category matrix for predictions cannot generate better results than fusing these resources together.

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