TRecSo: Enhancing Top-k Recommendation With Social Information

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ABSTRACT
Due to the data sparsity problem, social network information is often additionally used to improve the performance of recommender system. While most existing works exploit social information to reduce the rating prediction error, e.g., RMSE, a few had aimed to improve the top-k ranking prediction accuracy. This paper proposes a novel top-k oriented recommendation method, TRecSo, which incorporates social information into recommendation by modeling two different roles of users as trusters and trustees while considering the structural information of the network. Empirical studies on real-world datasets demonstrate that TRecSo leads to remarkable improvement compared to previous methods in top-k recommendation.

Keywords
Recommender System; Social network; Learning-To-Rank

1. INTRODUCTION
Recommending top-k items is the eventual goal in typical recommender system rather than accurately predicting the ratings of all items, as users are only interested to see top-k items [1]. Most recommender systems, however, mainly focus on accurately predicting the overall ratings [6, 5, 2, 12], and they are not well optimized for the task of finding top-k items. Several methods have been developed based on the Learning-To-Rank (LTR) perspective to provide accurate results at top-k [10, 14]. However, they still suffer from the data sparsity problem, that is, the recommendation is hardly accurate due to lack of observations (i.e., ratings) because users typically rate a small number of items. To tackle the data sparsity problem, researchers have tried to incorporate auxiliary information such as social network relationship, text reviews on items, etc. This paper focuses on incorporating the social network information of users in the top-k recommendation.

Two top-k recommendation methods have been developed to incorporate social network information based on the LTR approach [13, 14]. Specifically, Yao et al. [13] linearly combines a user's taste and her direct friends' tastes in optimizing the top-k recommendation. However, it does not utilize other important information hidden in social network such as the structural information or trustor-trustee relationship. Zhao et al. [14] optimizes the top-k recommendation from relative ordering that can be extracted from purchase history or browsing history, but it cannot handle numerical ratings directly. Note that numerical ratings usually contain much richer information on user's preference than relative ordering.

This paper proposes a novel LTR-based top-k recommendation method, TRecSo, which leverages the social network information to optimize top-k recommendation. TRecSo is distinguished from previous methods in that it models two different roles of users as trusters and trustees while considering the structural information of the network. Our experimental results on real-world datasets indicate that TRecSo considerably outperforms previous methods in top-k recommendation. Our implementation and experiment results can be found in our technical report [9].

2. METHOD
We first explain, in Section 2.1, how the social information is incorporated in TRecSo, and describe the objective function to optimize top-k recommendation in Section 2.2.

2.1 Incorporating Social Information
Assume that there are N users and M items, and R = [r_{ij}] is a N × M matrix where r_{ij} represents the rating that user i gave on item j. The rating matrix R is typically very sparse whose entries are mostly unknown. Then, the rating of user i on item j is predicted as follows:

\[
\hat{r}_{ij} = g(\mu + b_u_i + b_v_j + q_i^T (\alpha p_i + (1 - \alpha) w_i + |I_i|^{-\frac{1}{2}} \sum_{t \in I_i} y_t + |T_i|^{-\frac{1}{2}} \sum_{v \in T_i} x_v))
\]

(1)

where g(·) is the logistic function that bounds the range of predicted ratings; \(\mu\) is the average of all ratings; \(b_u_i\) and \(b_v_j\) represent the user and item biases, respectively; \(q_i\) represents the item latent vector; \(p_i\) and \(w_i\) represent the user latent vectors as truster and as trustee, respectively, which are also used to model the social information in Eq.(2); \(\alpha\) balances between the truster and trustee roles; \(I_i\) denotes the set of items rated by user i; \(y_t\) is the latent vector of item t, which models implicit influence of items rated by user i; \(T_i\) is the set of users that user i trusts (e.g., whom user i follows in social network); and \(x_v\) is the latent vector of whom user i
trusts, which models implicit influence of the users trusted by user $i$. $\hat{r}_{ij}$ in Eq.(1) will be used to optimize top-k recommendation in Section 2.2.

To tackle the data sparsity problem, social network information is modeled in TRecSo as follows. Given an asymmetric social relation matrix $S = \{s_{iv}\}, s_{iv} \in \{0, 1\}$ where $s_{iv}$ indicates whether user $i$ trusts (or follows) user $v$ or not, the unknown relationship $\hat{s}_{iv}$ between user $i$ and $v$ can be estimated as follows:

$$\hat{s}_{iv} = g \left( b_{vi} + b_{uw} + w_{i}^{T}p_{i} \right) \quad (2)$$

where $b_{vi}$ and $b_{uw}$ represent the trustor and trustee bias, respectively. By sharing the term $p_{i}$ and $w_{i}$ in Eq.(1) and (2), and by simultaneously learning both latent models, we are able to properly model the different roles of users as trusters and trustees. Note that our method can be generalized to the case where the social relations are symmetric, i.e., Friendship.

To reflect the structural information of the network, $s_{iv}$ is adjusted based on the degree of nodes such that it gives lower weights to those who trust many users and gives higher weights to those who are trusted by many users:

$$s_{iv} = \sqrt{\frac{\text{Outdegree}\left(v_{i}\right)}{\text{Indegree}\left(v_{v}\right) + \text{Indegree}\left(v_{i}\right)}} \times s_{iv} \quad (3)$$

where $v_{i}$ and $v_{v}$ are nodes for user $i$ and user $v$ in the network, respectively [5]. It is worth noting that the model performance has actually improved by this adjustment in the experiments [9].

2.2 Top-k Optimization

To optimize top-k recommendation, we formulate our objective based on top-one probability, $P_{i}(C_{j}) = \sum_{C_{j} \in \hat{C}_{i}} \exp(C_{j}) / \sum_{C_{j} \in \hat{C}_{i}} \exp(C_{j})$, which models the probability of an item scored $C_{j}$, being ranked on the top-one position in user $i$’s ranked list $l_{i}$ [1]. By utilizing the top-one probability, we are now able to formulate the objective function aiming at minimizing the uncertainty between the training list and the predicted list by using cross-entropy measure as follows, which can be interpreted as listwise ranking prediction:

$$L = - \sum_{i=1}^{N} \sum_{j \in T_{i}} P_{i}(r_{ij}) \log P_{i}(r_{ij}) - \lambda_{0} \sum_{i=1}^{N} \sum_{v \in T_{i}} P_{i}(s_{iv}) \log P_{i}(s_{iv}) \quad (4)$$

where $\lambda_{0}$ is a parameter that controls the importance of social regularization. Having formulated the non-convex objective function as shown in Eq.(4), we compute the gradient of each latent vector, i.e., $p_{i}$, $q_{i}$, $w_{i}$, $x_{i}$, $b_{vi}$, $b_{uw}$, and learn them by stochastic gradient descent [7] from which we obtain the local minimum.

3. EXPERIMENTS

Dataset: We used three public real-world datasets for evaluation (Table 2). The social relations between users are asymmetric in all three datasets. More details about data statistics and experiment results can be found in our technical report [9].

Setup: We compared TRecSo with six state-of-the-art methods that fall into one of three categories: 1) Traditional CF: ItemKNN, OCCLF [8], BPRMF [10], ListRank [11], SBPR [14], SoRank [13]; 2) Ratings-only-based methods: OCCF, BPRMF, ListRank, and Social network based methods: SBPR, SoRank. We set $\alpha = 0.5$, $\lambda = 0.01$, $\lambda_{0} = 0.01$, and $\lambda_{t} = 0.8$ for TRecSo, and the parameters for all the other baseline sets are set to their best performing parameters. Note that latent dimensions of 5 and learning rate of 0.01 are used for all the experiments. For fair comparison, we used the same experimental protocol as in [15].

Results: Table 1 shows that our method TRecSo, consistently outperforms all the state-of-the-art methods for all datasets. Note that $\forall$ in Table 1 denotes the number of items for each user in the training data.

4. CONCLUSION

This paper proposes TRecSo, a novel matrix factorization based recommendation method that optimizes the top-k ranking prediction accuracy by additionally considering the social network information. Specifically, TRecSo integrates the social network information into the Learning-To-Rank (LTR) based objective function for recommendation. Comprehensive experimental results show that TRecSo significantly outperforms the state-of-the-art algorithms in the top-k ranking accuracy of recommendation.

5. REFERENCES