Recommendation Algorithm Based on Directed Interaction Influence from Link Prediction and User Trust: Postprint

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Abstract

To address the issues of traditional recommendation algorithms that neglect the impact of social network structural tightness on user trust propagation and lack social psychological explanations, this paper proposes a recommendation algorithm based on link prediction, directed interactive influence, and user trust. First, a comprehensive similarity integrating user preference behavior and social circles is utilized to identify the similar friend circles of target users. Second, the directed interactive influence between target users is obtained by combining the node gravity index and directed influence factor. Then, a comprehensive user trust value, derived from directed interactive influence and user rating trust, is employed to identify trustworthy similar user sets within the target user's similar friend circles, which effectively improves recommendation accuracy. Finally, recommendations are generated. The results demonstrate that the proposed recommendation method achieves significant performance improvements over previous social network recommendation algorithms.

Full Text

Preamble

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Recommendation Algorithm Based on Link Prediction for Directed Interaction Influence and User Trust
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Abstract: Traditional recommendation algorithms often neglect the impact of social network structural tightness on user trust transmission and lack social psychological explanations. To address these issues, this paper proposes a recommendation algorithm based on link prediction that incorporates directed interaction influence and user trust. First, the algorithm identifies a target user' s similar friend circle using integrated similarity that combines user preference behavior and social circles. Second, it obtains directed interaction influence between target users by combining node gravity index and directed influence factors. Then, it identifies a trustworthy similar user set within the target user' s similar friend circle using comprehensive user trust values derived from directed interaction influence and user rating trust, which effectively improves recommendation accuracy. Finally, recommendations are generated. Experimental results demonstrate that the proposed method achieves significant performance improvements compared to previous social network recommendation algorithms.

Keywords: social network; score trust; directed interaction; link prediction

0 Introduction

Many scholars have introduced trust into e-commerce recommendation systems to alleviate issues such as recommendation accuracy and data sparsity. Li Liang et al. [?] proposed linearly weighting rating trust and preference trust to improve trust calculation methods, thereby enhancing recommendation accuracy. Ding Xiaohuan et al. [?] proposed a tensor decomposition recommendation algorithm that integrates friend relationships and tag information, demonstrating that incorporating friend relationships can improve recommendation accuracy. Zhu et al. [?] mined unknown trust relationships based on existing trust networks and different trust propagation methods, but this approach relied solely on recorded trust network information while ignoring interaction information between users. Liben-Nowell et al. [?] categorized similarity metrics into node-based and path-based metrics and analyzed the effectiveness of several metrics for link prediction in social networks.

The integration of recommendation systems and social networks has advanced personalized recommendation to a new stage. It is well known that people are more likely to accept recommendations from friends and experts. Therefore, incorporating user trust and interaction influence into recommendation algorithms provides a social psychological explanation for user social behavior. This recommendation algorithm treats user trust fused with directed interaction influence as a crucial factor affecting recommendations: (a) This paper combines the RA index (Resource Allocation index) [?] and AA index (Adamic-Adar index) [?] to propose a node interaction influence prediction method—the directed node gravity index. The directed node gravity index considers not only the degree of common neighbor nodes between two predicted nodes but also the impact of the small network formed by the predicted nodes and their common neighbors on predicting user interaction influence. Since each user has different interests and varying willingness to accept influence from others, this paper also considers the directionality of interaction influence [?]. (b) Additionally, it considers user trust across the entire recommendation system, calculating user trust from two factors: user activity and rating objectivity.

The main recommendation process of this paper is as follows: First, identify the target user' s similar neighbor set based on integrated similarity of preference behavior and social circles, then select top-k users with high recommendation trust values from this similar neighbor set for recommendation to the target user.

1.1 Typical Link Prediction Methods

In complex network link prediction research, network link prediction methods have become a hot topic. Link prediction refers to predicting the likelihood of a connection between two nodes that are not yet connected, based on known network nodes and structural information [?]. Typical RA and AA indices incorporate common neighbor node degree information when calculating node similarity and have achieved good prediction results. The RA index [?]: This algorithm assumes that each node in the network has certain resources that are equally distributed to its neighbors. For two unconnected nodes x and y, resources can be transferred from node x to node y through their common neighbors as transmission media. The amount of resources received by node y is defined as the similarity between nodes x and y, denoted as the RA index. The AA index [?]: This algorithm is based on the idea that common neighbors with smaller degrees contribute more to similarity than those with larger degrees. Node similarity is defined accordingly as the AA index.

These two indices only consider the number of common neighbors and their degrees between two predicted nodes, without deeply investigating the structural tightness of the small network formed between the predicted users and their common neighbors, nor the impact of node in-degree/out-degree directionality on prediction results.

1.2 Measurement of Friend Trust

Trust is a metric obtained by collecting and analyzing interaction behaviors between users to measure the closeness of friend relationships. Previous studies on user trust generally considered user rating recognition and rating accuracy. Rating recognition represents the degree to which a user's ratings are recognized by the public, while rating accuracy represents how close a user' s ratings are to the average rating of an item by the public. These methods simply consider these two factors, resulting in a one-sided approach that leads to inaccurate recommendations and fails to mine potential trusted friends.

1.3 Collaborative Filtering Algorithm and Similarity Calculation

The traditional collaborative filtering recommendation algorithm proceeds as follows: (a) Calculate user similarity based on the user-item rating matrix; (b) Select neighbor users based on similarity; (c) Generate predicted scores based on neighbor users; (d) Produce recommendations. This paper' s similarity calculation includes:

(a) Preference-based user similarity. Following the TF-IDF algorithm approach [?], this paper calculates the weight of item tags for user interest objects. The calculation formula is shown in Equation (1). $TF_{i,t}^{u,l}$ represents the frequency of tag t appearing in user u' s rated items; $IDF_{i,t}^{u,l}$ represents the discriminative ability of tag t in all users' rated item models. Their calculation methods are shown as $TF_{i,t}^{u,l} = \frac{num_{i,t}^{u,l}}{num_{i}^{u,l}}$ and $IDF_{i,t}^{u,l} = \log\frac{usernum}{ltnum}$, where $num_{i,t}^{u,l}$ represents the number of times user u uses tag t; $usernum$ is the total number of users in the recommendation system; $ltnum$ is the number of users who have used tag t. In summary, the item weight based on the tag system is $w_{i,t}^{u,l}$ as shown in Equation (4). The more similar the interest tags between users, the more similar their lifestyles and interests. This paper determines user social circle similarity by calculating the number of common friends between two users ($friend_u$ represents user u' s friend set).

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2 Recommendation Algorithm Based on Directed Interaction Influence and User Trust

The RUTI-CF algorithm consists of two progressive recommendation processes: first, clustering analysis centered on the target user to form a similar user set, then identifying trustworthy similar users from this set for recommendation. The algorithm model is shown in Figure 1.

[Figure 1: see original paper]

Figure 1. RUTI-CF algorithm model

2.1 Integrated Similarity of Preference Behavior and Social Circle

In real life, people are more willing to accept recommendations from friends in their social circles and prefer recommendations from those with similar personalities and hobbies. Improved similarity calculation is key to recommendation algorithms. With the continuous development of social networks, interactive users play increasingly active roles. This paper considers user similarity calculation beyond typical purchase, rating, and tagging behaviors, also incorporating preference behaviors of other online virtual friends in the friend circle. Users' decisions are influenced by these users to a certain extent.

Based on the above considerations, this section proposes a similarity measure combining user preference behavior and social circles. On one hand, the sparsity of user-tag data and item-tag data determines that user similarity will also suffer from sparsity issues. On the other hand, analyzing similarity based on user social circles reveals that users within the same social circle are more closely connected. In social networks, both user preference behavior and social circles contribute significantly to user similarity calculation. Based on relevant research, when both preference-based similarity ($sim_{tag}(u_i, u_j)$) and social circle-based similarity ($sim_{social}(u_i, u_j)$) exist, this paper uses the harmonic mean to fuse them; otherwise, it takes the maximum of the two similarity values. This effectively alleviates data sparsity in the user similarity matrix. The integrated calculation is shown in Equation (7).

Let I_u represent user u' s rated item set. The preference-based user similarity ($sim_{tag}(u_i, u_j)$) is calculated as shown in the formula. In social networks, if two users have highly overlapping social circles, they are likely to establish friend relationships. To discover potential friends using social circles, we must first identify social circles, i.e., achieve automatic friend grouping. The larger the intersection of two users' "friend circles," the more similar they are. Based on the above similarity calculation methods, this paper can obtain a small, ego-centered similar user network structure for each user in the social network. Next, this paper will measure the recommendation trust value of each similar user in this circle using integrated user rating behavior trust relationships and user node influence.

2.2.1 User Trust

1) User Activity. In recommendation systems, user activity [?] varies significantly and can implicitly infer the likelihood of a user' s interest in unrated items. Higher user activity suggests a lower probability of interest in unrated items. Therefore, this paper introduces user activity as a factor to measure the credibility of user rating behavior. The proposed user activity ($Activity_{u,item}$) is defined as $Activity_{u,item} = \log \frac{n_{u,item}}{user_{item}}$, where $n_{u,item}$ represents the number of times user u rates item $item$; $user_{item}$ represents the number of users who rated item $item$. The more times user u rates item $item$, the higher their activity and authority in this domain. Additionally, if a user' s friends rate the item more frequently, it indicates greater comment influence and 传播 influence on other friends, suggesting deeper understanding of the item' s domain and higher rating credibility; conversely, rating credibility is lower.

2) Rating Objectivity of User u on Item $item$. A high trust level only indicates that a user is generally trustworthy with credible ratings overall, not that every rating is trustworthy and objective. This issue reflects the credibility of a user' s evaluation of a single item. Considering that randomness in user scoring affects rating objectivity, the rating objectivity ($Objectivity_{u,item}$) is defined as $Objectivity_{u,item} = 1 - \frac{|r_{u,item} - \bar{r}_{item}|}{r_{max} - r_{min}}$, where $r_{u,item}$ represents user u' s rating value for item $item$; $\bar{r}_{item}$ represents the average rating of item $item$ by all users in the social network; r_{max} represents the highest rating value; r_{min} represents the lowest rating value. The closer a user' s rating is to the mean rating, the closer the objectivity value is to 1, with values ranging between 0 and 1.

From user activity and rating objectivity, we can calculate user u' s rating accuracy in a certain domain. The greater the activity and the more objective the rating, the higher the rating value and trustworthiness in this domain. The trust degree between recommended users and target users is derived as $Trust^{rating}_{u_i,u_j} = \frac{\sum_{item \in I_{u_i} \cap I_{u_j}} Scored\_Value_{u_i,item}}{|I_{u_i} \cap I_{u_j}|}$.

2.2.2 Directed User Interaction Influence Based on Link Prediction

In social networks, users with common items are considered neighbor nodes. The degree of two neighbor nodes is defined as $d_{ij} = 1$ if $I_{u_i} \cap I_{u_j} \neq \emptyset$ (indicating a directed edge from node u_i to u_j), otherwise $d_{ij} = 0$. When measuring the possibility of trust transmission between nodes b and c, the proposed interaction influence considers not only the degree of common neighbors between the two predicted nodes but also the structural tightness of the small network formed by the predicted nodes and their common neighbors. Therefore, this paper uses the node gravity index (S_{u_i,u_j}) to predict interaction influence between nodes u_i and u_j, defined as $S_{u_i,u_j} = \frac{\sum_{a \in C} e_{a,u_i}}{k_{a,u_i} \cdot \varphi}$, where e_{a,u_i} is the number of links between node a and other common neighbors and nodes u_i and u_j; k_{a,u_i} is the degree from node a to u_i; φ is the degree of common neighbor nodes of u_i and u_j; C is the set of user nodes in the small network formed by nodes u_i, u_j, and their common neighbors; D is the set of all user nodes in the entire social network.

[Figure 2: see original paper]

Figure 2. Interactive influence diagram

As shown in Figure 2, the interaction influence transmitted from node a to node b (I_{ab}) is unbalanced with that from node b to node a (I_{ba}), demonstrating the directionality of interaction influence. Additionally, node a exerts unidirectional interaction influence I_{ac} on node c. Due to the transitivity of interaction influence, node b will exert certain influence I_{bc} on node c. We can calculate I_{bc} to predict the likelihood of trust link establishment from node b to c. Interaction influence between nodes enhances trust relationship establishment.

This paper treats a user node' s rated item categories as interest preference points, so common rated item categories between user nodes can be considered shared interest preference points. Target users can influence other users who may establish trust relationships through these shared interest preference paths. The directed influence factor ($\gamma(u_i, u_j)$) is calculated based on the proportion of common rated items to reflect differences in mutual influence between users. When target users and potential trust users share more common rated items, and these constitute a higher proportion of the target user' s total rated items, it indicates multiple interest preference paths for influence, resulting in higher influence; conversely, influence is lower. The directed influence factor is defined as $\gamma(u_i, u_j) = \frac{|I_{u_i} \cap I_{u_j}|}{|I_{u_i}|}$.

Considering the differences in mutual influence between user nodes, this paper modifies the influence measurement method. The directed interaction influence ($Dir^I_{u_i,u_j}$) is defined as $Dir^I_{u_i,u_j} = S_{u_i,u_j} \times \gamma(u_i, u_j)$, where S_{u_i,u_j} is the interaction influence between nodes u_i and u_j, and $\gamma(u_i, u_j)$ is the directed influence coefficient. Their product yields the directed interaction influence, i.e., the directed edge weight from node b to c in social network G (dashed line indicates).

As shown in Figure 2, in small social network A formed by nodes a, b, c and small social network B formed by nodes c, d, e, f, we calculate the likelihood of trust link establishment from node b to c using Equation (14) as $S_{b,c} = \frac{2}{3}(a) = \frac{2}{3}$. Similarly, node d' s likelihood to c is $S_{d,c} = \frac{3}{4}(f) + \frac{2}{3}(e) = \frac{17}{12}$. The interaction behaviors of nodes b, c, d are shown in Figure 3.

[Figure 3: see original paper]

Figure 3. Schematic point of directional influence coefficient

From Equation (13), the directed influence factor from node b to c is $\frac{2}{7}$, and from node d to c is $\frac{3}{7}$. Using Equation (17), the directed interaction influence from node b to c is $\frac{2}{3} \times \frac{2}{7} = \frac{4}{21}$, while from node d to c is $\frac{17}{12} \times \frac{3}{7} = \frac{17}{28}$. Since social network B has more intensive interaction behaviors than network A, its structure is tighter, making it easier for node d to establish trust with c than node b.

2.2.3 Comprehensive Recommendation Trust

Based on the above research, the recommendation trust ($trust_{u_i,u_j}$) combining online social network user trust ($Trust^{rating}_{u_i,u_j}$) and interaction influence ($Dir^I_{u_i,u_j}$) is calculated as $trust_{u_i,u_j} = \alpha \cdot Trust^{rating}_{u_i,u_j} + (1-\alpha) \cdot Dir^I_{u_i,u_j}$, where α ($0 \leq \alpha \leq 1$) balances the impact of user trust and interaction influence on recommendation trust values, with its specific value determined by the social network context.

3 Recommendation Algorithm Based on Directed Interaction Influence and User Trust

This paper calculates user similarity values using the integrated preference behavior and social circle method to find the target user's "friend circle" and obtain the neighbor set NB. The recommendation results are generated as follows:

Assume the target user u' s "friend circle" forms set NB. For any $v \in NB$, calculate the comprehensive recommendation trust value between target user u and friend v in the friend circle, fusing directed interaction influence and user trust. Use the top-k method to obtain the trustworthy neighbor set $TNB = \{u_1, u_2, ..., u_k\}$. Then combine their historically rated item sets I_i $(i = 1, 2, ..., k)$ into a new set *Recommend-Item* for recommendation to the target user.

4.1 Experimental Dataset

This experiment uses the Last.fm dataset. Before evaluation, the dataset was filtered to include only users who had tagged at least 10 musicians, resulting in 881 users with their friend information and tagging behavior records. The data was then divided into training and test sets. Cross-validation was performed five times, and the average results were calculated.

4.2 Experimental Evaluation Metrics

Precision, recall, and F1-measure are three important metrics in recommendation systems. Precision represents the proportion of successfully recommended items, with higher values indicating better models. Recall represents the proportion of recommended friends relative to friends in the test data, with higher values indicating better performance. The F1-measure comprehensively evaluates both metrics, as they may conflict in some cases. Higher F1-measure values indicate superior algorithm performance. The formulas are:

$precision = \frac{|like_{recommend}|}{|n_{recommend}|}$

$recall = \frac{|like_{recommend}|}{|n_{test}|}$

$F1\text{-}measure = \frac{2 \times precision \times recall}{precision + recall}$

where $n_{recommend}$ represents the number of recommended items, n_{test} represents the number of items in the test set, and $like_{recommend}$ represents the number of recommended items liked by the user.

4.3 Experimental Results Analysis

This experiment validates reasonable values for α and K, then compares the proposed algorithm with other recommendation algorithms under optimal values.

1) Impact of Weight Value α. Experiments were conducted with α values of 0.0, 0.1, 0.2, ···, 1.0. To eliminate the impact of neighbor quantity, neighbor counts were set from 2 to 10 (9 groups). Table 1 shows the impact of different α values on RUTI-CF algorithm accuracy on the Last.fm dataset. When K is fixed, as α increases from 0.0, the accuracy of RUTI-CF algorithm shows a consistent trend: it first rises gradually, reaches a peak, then declines gradually. The best accuracy occurs at $\alpha = 0.6$, indicating a 3:2 ratio of user trust to interaction influence impact on final recommendations. This shows that in a similar user "friend circle,"trusted friends' ratings have greater influence than interaction influence. When α varies between 0.8 and 1.0, recommendation accuracy drops sharply. Particularly at $\alpha = 1.0$ (considering only user node influence), accuracy decreases by 10%-20% compared to $\alpha = 0.9$, demonstrating that ignoring interaction influence significantly reduces recommendation accuracy, indicating that interaction influence substantially promotes trust relationship establishment.

2) Impact of Top-K Value. Based on the recommendation generation method, K was set from 2 to 10 to observe accuracy variation patterns. Table 1 results show that regardless of α, as K increases, RUTI-CF algorithm accuracy first rises, peaks, then declines. In this experimental environment, accuracy continuously rises when K varies from 2 to 5, reaches maximum at $K = 6$, then declines when K varies from 6 to 10. This demonstrates that neighbor quantity affects recommendation quality, but more neighbors do not necessarily yield better quality. For this dataset, $K = 6$ produces optimal results.

3) Comparison of Different Algorithms. To validate effectiveness, RUTI-CF was compared with FT-CF algorithm (hybrid collaborative filtering based on friendships and tags) [?], FRSN-CF algorithm (friend recommendation methods in social networks) [?], Trust_CF (considering only online social network user trust), and Influence_CF (considering only user interaction influence). Experiments yielded accuracy and F1-measure values shown in Figures 4 and 5.

[Figure 4: see original paper]

Figure 4. Accuracy of each algorithm under different K values

[Figure 5: see original paper]

Figure 5. F1-measure value of each algorithm under different K values

As shown in Figures 4 and 5, all algorithms show consistent variation patterns across metrics. For accuracy, it first increases then decreases with K, confirming the optimal $K = 6$ conclusion. Recall continuously increases with K, but the growth rate slows and gradually stabilizes. The RUTI-CF algorithm outperforms others in both accuracy and F1-measure. Compared with FT-

CF, which also considers friend relationships and tags for similarity, RUTI-CF achieves higher accuracy and F1-measure, demonstrating that integrating user trust and interaction influence for comprehensive recommendation trust evaluation is more precise. Compared with FRSN-CF, which uses friend interaction behavior for recommendations, and Trust_CF, which considers only trust, experimental results show RUTI-CF' s superiority, indicating that considering only trust relationships is one-sided, while simultaneously considering directed interaction influence yields superior recommendation performance.

5 Conclusion

Experimental results demonstrate that the RUTI-CF algorithm exhibits good recommendation performance, showing that integrating online social network user trust and user influence provides a more comprehensive evaluation of comprehensive recommendation trust. By measuring undirected interaction influence and combining it with directed influence coefficients, this paper proposes directed interaction influence for more precise comprehensive recommendation trust. The recommendation model considers both direct social rating trust and indirect impact of user node interaction influence on trust relationship establishment, making it more consistent with social logic and achieving higher accuracy and recall.

This paper primarily discusses collaborative filtering for static networks. As the number of users, items, and tags in the system continues to grow, data sparsity issues may degrade algorithm performance. Future research will focus on combining temporal network characteristics to analyze user similarity patterns across different time windows, proposing effective recommendation algorithm models for dynamic networks.

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Note: Figure translations are in progress. See original paper for figures.