Research on Personalized Recommendation Algorithms Based on Multi-faceted Trust Relationships in Tag Clusters Postprint

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Date: 2017-11-08T00:00:00+00:00

Abstract

[Objective] In personalized recommendation based on multi-faceted trust relationships, this study addresses the problem of low recommendation accuracy caused by the difficulty in defining facets and the limitations of traditional trust strength calculation methods. [Method] We propose a method for defining multi-faceted trust relationships based on tag clusters. Building upon tag clusters obtained through tag clustering, we incorporate the TF-IDF concept and Pearson similarity to define inter-cluster and intra-cluster trust relationships, construct a trust tensor that facilitates reflecting trust strengths across different facets, and integrate it into a personalized recommendation algorithm based on tensor decomposition models. [Results] Simulation experiments based on the Last.fm dataset demonstrate that the personalized recommendation algorithm proposed in this paper achieves good performance across accuracy, recall, and F1-score metrics, with an average improvement of 2.29% in F1-score. [Limitations] The simulation experiments have not been further validated on datasets from other domains, such as Weibo, Twitter, etc. [Conclusion] The personalized recommendation algorithm based on multi-faceted trust relationships of tag clusters improves recommendation accuracy by effectively defining and comprehensively, objectively quantifying trust relationships between users, thereby facilitating the provision of more satisfactory resources to users in social network environments.

Full Text

Preamble

Research on Personalized Recommendation Algorithm Based on Multi-faceted Trust Relationships of Tag Clusters
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Abstract

[**Objective**] This paper addresses the low recommendation accuracy in personalized recommendation systems based on multi-faceted trust relationships, which stems from difficulties in defining facets and limitations of traditional trust strength calculation methods. [**Methods**] We propose a novel method for defining multi-faceted trust relationships based on tag clusters. Building upon tag clusters obtained through clustering, we incorporate TF-IDF principles and Pearson similarity to define inter-cluster and intra-cluster trust relationships, constructing a trust tensor that effectively reflects trust intensity across different facets. This tensor is then integrated into a personalized recommendation algorithm based on tensor decomposition models. [**Results**] Simulation experiments using the Last.fm dataset demonstrate that our proposed personalized recommendation algorithm achieves superior performance across precision, recall, and F1 metrics, with an average improvement of 2.29% in F1 value. [**Limitations**] The simulation experiments have not been validated on datasets from other domains, such as Weibo or Twitter. [**Conclusions**] The personalized recommendation algorithm based on multi-faceted trust relationships of tag clusters effectively defines and comprehensively quantifies trust relationships among users, thereby improving recommendation accuracy and facilitating more satisfactory resource provision in social network environments.

Keywords: Personalized Recommendation; UGC Tag; Tensor Decomposition; Multi-faceted Trust

Classification Numbers: F224.39; TP391; TP181

Introduction

UGC (User Generated Content) tags serve as crucial resources in Internet-based social environments of the Web 2.0 era, embodying the collective intelligence of mass users while reflecting both user interests and characteristics of online resources. Consequently, UGC tags have become an important means for effectively organizing user and resource information. Tags not only act as a bridge connecting users and resources, but similar tags also reflect certain user interests and the resources corresponding to those interests. Meanwhile, friendship relationships in social networks provide valuable information for recommendation systems, as users tend to trust recommendations from their friends. Numerous studies have demonstrated that trust-based recommendation systems can provide additional user similarity information and improve recommendation accuracy. Therefore, considering the common interest preferences among friends reflected in the vast amount of tag information on social networks is of significant importance for improving recommendation algorithm accuracy.

Research on trust relationships has revealed that due to the complex structure of trust networks, friends are not necessarily similar users, and the differences can be substantial. Therefore, trust relationships are not suitable for standalone use in personalized recommendation and are typically employed as a supplement to baseline recommendation systems. Accordingly, Ding Xiaohuan et al. constructed a linear model integrating item-based trust and tag-based trust on top of tensor decomposition models, thereby improving recommendation accuracy. Additionally, existing trust-based recommendation systems mostly consider only a single aspect of trust relationships among users. In reality, both online and offline friendships are often established based on certain interests rather than complete similarity across all interests. Distinguishing user trust across different interest facets can provide more precise additional information for recommendation systems. In academia, this type of trust relationship across different interest facets is termed multi-faceted trust.

Multi-faceted trust relationships have been studied in personalized recommendation research. Quinn et al. investigated recommendation accuracy based on multi-faceted trust using actor recommendations as an example through questionnaires, finding that higher trust risk leads to lower accuracy. Peng et al. categorized blog posts into six major classes on a blog website, collected user ratings for each post through online experiments, obtained friendship information through online surveys, and thereby derived multi-faceted trust relationships among friends. Such studies typically require subjective division of resources into multiple facets, which is prone to errors and lacks rationality when facing large volumes of diverse resources in actual blog-based social networks.

Tang et al. also divided all resources into several categories as facets, constructing a trust tensor based on user rating information for resources. They elaborated on the definition process of trust tensors under multi-faceted trust, constructed a user vector space model under multi-faceted trust where user ratings in each facet serve as user vectors, calculated trust strength among users through cosine similarity as weights integrated into collaborative filtering algorithms, and linearly integrated resource-based collaborative filtering algorithms under multi-faceted trust, effectively improving prediction accuracy. However, their approach has two main limitations: First, their research website already had resources categorized into different classes, but for social networks like Weibo and Twitter without resource classification, the problem of facet definition remains to be solved. Second, cosine similarity has limitations in calculating trust relationships: resources belonging to the same facet should have certain similarities, but if two users rate multiple resources within the same facet with few common rating records, the trust relationship calculated through cosine similarity tends to be smaller and approaches 0 as the resource volume increases, which clearly contradicts reality.

In summary, this paper first proposes a method for constructing multi-faceted trust relationships among users based on tag clusters to efficiently solve the difficult problem of facet definition. Specifically, we employ spectral clustering based on integrated tag co-occurrence to generate tag clusters that serve as the basis for facet definition to construct trust tensors, which are then integrated into personalized recommendation algorithms based on tensor decomposition models. Second, we define inter-cluster and intra-cluster trust relationships to avoid the limitations of cosine similarity in calculating trust strength. Finally, we verify the improved algorithm through simulation experiments.

2. Spectral Clustering Based on Integrated Tag Co-occurrence

Clustering tag data serves two purposes: first, it reduces tag redundancy and semantic ambiguity before tensor decomposition, eliminating noisy data while highlighting semantic relationships, which benefits recommendation accuracy improvement; second, the resulting tag clusters provide an important basis for obtaining trust facets.

Regarding clustering algorithm selection, Li et al. proposed an improved method combining tag co-occurrence with spectral clustering, which divides tag similarity into individual co-occurrence similarity and group co-occurrence similarity as input for spectral clustering. This approach shares the core idea with Li Ruimin et al. that if a user and an item share more common tags, the association between them is stronger. Individual co-occurrence similarity 刻画 s the most fundamental connection between two tags, while group similarity enhances semantic relationships among tags and can be considered a supplement to individual similarity. By combining individual and group co-occurrence similarities through integrated co-occurrence similarity, the similarity relationships among tags can be better expressed. Compared with traditional clustering methods, this approach has the advantage of not requiring the division of triples into binary groups to define tag similarity, thus completely preserving the semantic relationships among users, tags, and resources. Additionally, the graph theory-based spectral clustering algorithm is more conducive to discovering irregular clusters, thereby better achieving clustering of scattered tags, highlighting semantic relationships, solving tag redundancy and semantic ambiguity problems, and improving recommendation accuracy.

Therefore, this paper introduces the integrated co-occurrence-based spectral clustering method for data preprocessing before tensor decomposition. While solving tag redundancy problems, the resulting tag clusters also provide a foundation for defining trust relationships among users. Tags within each cluster have strong similarities and, as features connecting users and resources, represent certain resource themes that users like and certain interests of user groups.

3. Definition of Multi-faceted Trust Relationships Based on Tag Clusters

Based on effective cleaning of tag data through spectral clustering and an improved tensor decomposition model that highlights semantic relationships among <user, tag cluster, resource>, integrating trust relationship information from social networks will further improve recommendation accuracy. However, in reality, trust relationships among users are typically established only on certain or even single aspects of common interests. For example, if two users a_u and b_u both like folk music, they may establish a trust relationship, but if a_u also likes rock music while b_u does not, recommending all music liked by a_u to b_u based on this simple trust relationship would be inappropriate. Compared with single-faceted trust relationships, constructing trust tensors to define user trust relationships across different facets is more conducive to effectively improving recommendation accuracy.

In social networks, tags have complex and diverse semantics. Dividing them into different facets and allocating all tags to these facets according to certain rules is difficult to guarantee accuracy through expert or manual methods alone and may cause semantic confusion. As mentioned earlier, tag clustering can automatically and accurately divide tags into different clusters, and the integrated co-occurrence-based spectral clustering algorithm relatively completely covers all user interest preferences. Therefore, we consider using the resulting tag clusters as facets reflecting different user interests, extending pairwise multi-faceted trust relationships among users to all users to form a three-dimensional <user, tag cluster, user> trust tensor.

The trust tensor measures trust strength among users rather than relationships between tags. Meanwhile, the tag clustering-based trust relationship definition effectively solves the facet division problem, and the tag cluster-based facet method is objective and efficient.

Let the trust tensor be $\mathcal{T}_1 \in \mathbb{R}^{I \times C \times I}$, where I and C represent the number of users and tag clusters in the dataset, respectively. Let the elements within the tensor be $t_{a,j,b} \in [0,1]$, representing the trust strength of user a_u towards user b_u on cluster j_C. A higher value indicates a tighter trust relationship or greater similarity between the two users on the same interest facet. If a_u and b_u are not friends, then $t_{a,j,b} = 0$.

4. Construction of Trust Tensor Based on Inter- and Intra-cluster Trust Relationships

Defining the elements of the tensor, i.e., trust strength, is the core of constructing multi-faceted trust tensors. This paper divides it into intra-cluster and inter-cluster trust relationships. In fact, in Ad Hoc networks, numerous achievements have defined trust relationships among network nodes through inter-cluster and intra-cluster trust concepts. Jin Yu et al., in their research on network malicious node filtering technology, proposed the concepts of intra-cluster and inter-cluster service trust based on a two-layer trust model (TLT), obtaining comprehensive service trust relationships among network nodes through linear weighting to quickly and effectively identify malicious nodes. Chen et al., to solve the problem of difficulty in establishing trust relationships among nodes due to dynamic changes in mobile Ad Hoc networks, divided the network into multiple node clusters with cluster heads and introduced the concept of intra-cluster trust to provide additional trust information for unfamiliar nodes. Trust among nodes in Ad Hoc networks can be obtained by examining historical transaction behaviors between nodes. However, in social network environments, UGC tags do not have direct connections, and the phenomena of multiple meanings for one tag and multiple tags for one meaning are widespread. Different users may use different tags within the same tag cluster or use the same tag across different tag clusters, thereby increasing the complexity of trust relationships among users. Thus, the definition of trust relationships among nodes based on node clustering in Ad Hoc networks is completely unsuitable for defining trust relationships among users based on UGC tags in social networks. Nevertheless, this paper draws on its ideas and proposes concepts of intra-cluster and inter-cluster trust relationships based on tag clusters as supplementary trust information to comprehensively and completely express the strength of trust relationships among users in social networks.

Calculating trust strength requires solving two key problems:

Problem 1: Most existing achievements calculate weights representing trust strength based on cosine similarity. If users a_u and b_u have both used tags from a certain tag cluster but their used tags are completely different, then even if they have used many tags from this cluster, their trust degree according to cosine similarity would be 0. However, after clustering, tags within the same tag cluster have certain similarities, so a_u and b_u should have some trust strength. Therefore, calculating tag cluster-based trust strength solely through cosine similarity would cause measurement distortion.

Thus, by defining inter-cluster trust relationships, we consider users' overall tagging preferences for tag clusters, which helps judge user correlations on individual clusters. The TF (Term Frequency) idea in TF-IDF is used to define word frequency in documents, where higher frequency words are more likely to express document content. This paper draws on the TF idea to define the frequency of tags in a tag cluster among all tags used by a user. Higher frequency indicates that the tag better represents the user' s main interest, i.e., $p_{u,j} = \frac{n_{u,j}}{n_u}$, where the numerator represents the number of times user i_u tagged in tag cluster j_C, and the denominator represents the number of times user i_u tagged in all tag clusters. Therefore, for users a_u and b_u, if they are friends, their common interest degree in a certain tag cluster is the inter-cluster trust relationship, which can be defined as:

$$IT_{a,b,j} = \frac{p_{a,j} \cdot p_{b,j}}{\|p_a\| \cdot \|p_b\|}$$

Problem 2: Inter-cluster trust relationships actually examine users' preferences for tag clusters, but is it also necessary to examine users' preferences for tags within clusters? In fact, considering only inter-cluster trust relationships is insufficient. The high sparsity characteristic of tag data in social network environments inevitably affects clustering effectiveness. In addition to cleaning data to reduce errors, we can also assist judgment by measuring tag usage within clusters. That is, combining intra-cluster trust relationships with inter-cluster trust relationships simultaneously reflects user similarity within and between clusters, which is conducive to completely expressing trust relationships among users across different facets.

Typically, based on constructing a vector space model (VSM) for tags, common cosine similarity, Pearson similarity, and Euclidean similarity formulas are used to calculate trust strength. However, Zhen et al. found that in tag systems, the method combining Pearson similarity with Sigmoid function can obtain more accurate results than other methods. Therefore, this paper uses this method to define the intra-cluster trust relationship between users a_u and b_u in cluster j_C, representing that users are more likely to have similarities in certain interests. Thus, users' friends can be considered similar users. Ding Xiaohuan et al. precisely based on this idea multiplied friend information by single-faceted trust strength and integrated it into the recommendation algorithm.

Therefore, this paper considers integrating the trust tensor $\mathcal{B}_1$ as weight for friend information into the original tensor model to provide additional information for target users.

Let any element in the fused tensor be $x'_{u,j,r}$, where $\omega'_{u,j,r}$ represents a fiber in the tensor, i.e., on facet j_C, $x'_{u,j,r}$ represents the final tagging situation of user u on resource r. $\omega_{u,j,r}$ and $\omega_{b_u,j,r}$ represent the number of times users a_u and b_u used tags in cluster j_C to tag resource k_i, respectively; $\bar{\omega}_{a_u,j}$ and $\bar{\omega}_{b_u,j}$ represent the average number of tags used by users a_u and b_u in cluster j_C.

To integrate factors on the same level but with different importance, linear addition is typically employed. This paper considers linearly combining inter-cluster and intra-cluster trust relationships through parameter $\alpha \in [0, 1]$ to balance the contributions of both parts to trust strength, obtaining trust relationships between users on a given tag cluster, i.e., any element in trust tensor $\mathcal{B}_1$ can be expressed as:

$$t_{a,j,b} = \alpha \cdot IT_{a,b,j} + (1 - \alpha) \cdot PT_{a,b,j}$$

Since inter-cluster trust reflects users' overall preferences for tag clusters, it plays a more important role than intra-cluster trust in calculating trust relationships among users. Therefore, we preliminarily determine that α should be greater than 0.5, with the optimal value to be obtained through subsequent simulation experiments.

5. Personalized Recommendation Algorithm Integrating Trust Tensor

Since spectral clustering based on integrated tag co-occurrence is performed before tensor decomposition, transforming the <user, tag, resource> ternary relationship into <user, tag cluster, resource>, we adapt the original <user, tag, resource> initial tensor by calculating the number of tags a user applies to a resource within the same tag cluster, forming a <user, tag cluster, resource> initial tensor. We then apply the HOSVD-HOOI algorithm to decompose the initial tensor, retaining 70% of the original information to obtain an approximate tensor.

The neighborhood-based collaborative filtering idea utilizes similar users' past behaviors to predict target users' preferences. Research shows that trust relationship information is suitable as a supplement to recommendation models. The trust strength between target user i_u and their friends under different facets is used as a weight to integrate friends' tagging records ($\omega_{b_u,j,r}$) for resource r in tag cluster j_C. After averaging, this serves as supplementary information added to the user' s own tagging records to obtain a corrected recommendation tensor.

From a practical usage scenario, when user i_u selects a tag j_t, the system queries the tag cluster j_C to which j_t belongs, then finds the top N resources with the highest $x'_{u,j,r}$ in the user' s tensor under target tag cluster j_C, and recommends them to the user, thus completing the recommendation.

6. Experiments and Results

6.1 Dataset Selection

The Last.fm dataset selected for this paper has been widely used since its release at the 5th International Conference on Recommender Systems in 2011. It includes tagging and listening records from 1,892 users on 17,632 artists between 2005-2011, generating 11,946 tags, 186,479 tagging behaviors, and 12,717 bidirectional friendship pairs (i.e., 25,434 unidirectional relationships).

To improve computational efficiency, we filtered the original dataset. First, to avoid the cold start problem, we retained only users, tags, and resources with relatively high occurrence frequencies, selecting users and artists with more than 70 tagging records. Second, to avoid the impact of malicious robot ratings on dataset quality, we filtered out users with more than 3,000 tagging records. Finally, we selected tags used more than 20 times to avoid the impact of high tag data sparsity on clustering effectiveness. The resulting core subset includes 444 users, 275 tags, and 372 artists, with 37,749 valid records in total, averaging 4.07 friends per user. We randomly selected 80% of the data as the training set and the remaining 20% as the test set.

In the training set, all users were randomly assigned a tag they had previously used. The algorithm generated a Top-N list for each user, which was compared with resources tagged by the corresponding user in the test set to obtain effective recommendation results, thereby calculating the algorithm' s performance metrics.

6.2 Performance Evaluation Metrics

Recommendation accuracy is a crucial indicator for evaluating recommendation algorithm performance. Currently, mainstream Top-N recommendation accuracy evaluation metrics include precision, recall, and F1 measure. Since the first two influence each other, we use precision-recall curves to qualitatively reflect accuracy trends. Additionally, the F1 measure, as the harmonic mean of both, can quantitatively reflect differences between algorithms. Therefore, we also select the F1 measure to evaluate system accuracy.

Simulation experiments were repeated 10 times, with the mean value of each metric within these 10 runs taken as the experimental result.

6.3 Parameter Optimization

The proposed recommendation algorithm has two main parameters that significantly affect the final recommendation results: the number of clusters and the α value.

The number of clusters has a certain impact on improving recommendation accuracy. Since the research purpose is to enhance recommendation accuracy by integrating multi-faceted trust relationships, simulation comparison experiments should exclude differences caused by clustering algorithms as much as possible. Therefore, all comparison algorithms are based on the same spectral clustering with identical cluster numbers. For the spectral clustering used in this paper, the optimal number of clusters can be determined as 5 by finding the optimal modularity metric.

The parameter α needs to be optimized through simulation experiments to find the optimal value that maximizes recommendation accuracy. We varied α from 0 to 1 in steps of 0.05, iteratively constructing new trust tensors and recommendation models, and calculating F1 values for different recommendation lengths ($N \in \{10, 15, \cdots, 50\}$). The mean F1 value for each iteration was then computed to plot the F1 variation curve with respect to α.

As shown in Figure 1 [Figure 1: see original paper], the simulation experiments confirm that inter-cluster trust is more important than intra-cluster trust for accuracy. As α increases, the weight of inter-cluster trust increases, and the F1 value shows an upward trend, reaching its maximum at $\alpha = 0.75$. This demonstrates that compared with traditional methods using cosine similarity to calculate trust strength (i.e., the formula when $\alpha = 0$), the improved algorithm can effectively enhance recommendation accuracy.

6.4 Comparison Algorithms Selection

The simulation experiments simulate a scenario where users obtain a Top-N list by selecting a previously used tag. We compare algorithm performance metrics as the number of recommended resources increases from Top10 to Top50 in increments of 5.

The performance comparison and algorithm selection principles are as follows:

(1) To compare recommendation accuracy before and after integrating user trust tensors, we select the tensor decomposition algorithm based on integrated co-occurrence spectral clustering without trust tensors (abbreviated as CoSCluTD) to verify the accuracy improvement of our proposed Multi-faceted Trust-CoSCluTD algorithm (abbreviated as MFT-CoSCluTD).

(2) To compare the impact of single-faceted versus multi-faceted trust relationships on recommendation accuracy, we select the recommendation algorithm based on single-faceted trust relationships without trust tensor fusion (abbreviated as ST-CoSCluTD), where user i_u' s final tagging situation for all resources on any facet j_C is as follows: $x'_{u,j,r} = \omega_{u,j,r}$.

6.5 Accuracy Comparison and Analysis

Figure 2 [Figure 2: see original paper] shows the simulation results of precision-recall curves, where each curve represents the precision and recall changes of an algorithm at different N values. When N is small, precision is high while recall is low; as N increases, precision decreases and recall increases. Curves closer to the upper-right corner indicate better recommendation performance.

Result 1: The MFT-CoSCluTD algorithm proposed in this paper generally achieves better precision and recall than the other two algorithms when recommendation length ranges from 10 to 50. Compared with CoSCluTD without trust relationships, MFT-CoSCluTD shows a stable accuracy improvement as recommendation length gradually increases, with an average relative precision improvement of 2.13% and an average recall improvement of 2.45%. This demonstrates that multi-faceted trust relationships can effectively identify user interests and provide additional information for recommendation systems.

Result 2: The CoSCluTD algorithm without trust relationships actually performs better than the ST-CoSCluTD algorithm considering single-faceted trust relationships, with the gap gradually decreasing as recommendation length increases. This indicates that single-faceted trust alone cannot reasonably define user trust relationships, and the incorporation of erroneous information interferes with the originally highlighted user-resource relationships, causing ST-CoSCluTD to recommend more resources unrelated to user interests. As recommendation length increases, the appearance of more relevant resources weakens the impact of erroneous information, reducing the gap.

Figure 3 [Figure 3: see original paper] compares the performance of the three algorithms on the F1 metric.

Result 3: Compared with CoSCluTD, MFT-CoSCluTD achieves an average relative precision improvement of 2.29% on the F1 metric, reaching a maximum improvement of 3.06% when $N = 50$. The algorithm' s recommendation accuracy advantage slightly increases with recommendation length N, further demonstrating that integrating multi-faceted trust relationships benefits recommendation accuracy improvement.

Result 4: Compared with CoSCluTD, ST-CoSCluTD shows an average F1 decrease of 6.61%, with the maximum decrease of 12.88% when $N = 10$. The decrease gradually diminishes as recommendation length N increases, further indicating that considering only single-faceted trust relationships is detrimental to recommendation accuracy improvement.

Simulation results show that the MFT-CoSCluTD algorithm achieves maximum F1 precision at $N = 20$, suggesting that the ideal recommendation length in practical applications should be $N = 20$.

Additionally, to avoid simulation results being affected by tag filtering, we conducted a comparative experiment between core subsets Tag8 (tags occurring more than 8 times) and Tag20 (tags occurring more than 20 times) under otherwise unchanged filtering conditions. The performance of our proposed MFT-CoSCluTD algorithm remained superior.

7. Conclusion

To address the accuracy degradation caused by tag redundancy and semantic ambiguity in UGC tags within tensor models, and to better utilize trust relationships, we propose a tag cluster-based trust tensor. Building upon integrated tag co-occurrence and spectral clustering to solve tag redundancy issues, we use the resulting tag clusters as the basis for defining trust facets, solving the current problem of difficult facet definition. For trust strength calculation, we divide trust relationships into inter-cluster and intra-cluster components, drawing on TF-IDF and Pearson similarity ideas to define the trust tensor, thereby addressing the limitations of cosine similarity in trust strength calculation. Finally, based on collaborative filtering principles, we integrate the trust tensor as supplementary information into the recommendation model after tensor decomposition. Experiments on the Last.fm dataset demonstrate that this method can effectively improve recommendation accuracy by fully utilizing tag data and friendship information.

With the popularization of online social networking sites, personalized recommendation based on tags and trust relationships will receive broader attention. Future work will mainly focus on further validating algorithm effectiveness across different datasets.

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Conflict of Interest Statement: All authors declare no conflict of interest.

Supporting Data: Supporting data is self-archived by the authors, E-mail: cmm@dhu.edu.cn.

[1] Xue Kangjie. train_{Tag20}.txt. Training dataset.
[2] Xue Kangjie. test_{Tag20}.txt. Testing dataset.
[3] Xue Kangjie. userfriend.txt. Friendship relationship dataset.

Author Contributions: Chen Meimei: Proposed research ideas and specific research plan, wrote and revised the paper; Xue Kangjie: Designed methods

and implemented simulations, wrote and revised the paper.

Received: 2017-02-20
Revised: 2017-03-31

Personalized Recommendation Algorithm of Multi-faceted Trust Tensor Based on Tag Clustering

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Abstract: [Objective] This paper aims to solve the low accuracy issue facing personalized recommendation algorithm of multi-faceted trust tensor based on tag clustering. [Methods] First, we proposed a new method to calculate multi-faceted trust based on tag clusters. Then, we introduced the TF-IDF and Pearson similarity to indicate strength of inter-cluster and intra-cluster trust. Finally, we built recommendation mechanism based on tensor decomposition to reflect the trust intensity from different facets. [Results] We examined the new algorithm with the Last.fm dataset. The precision, recall and F1 measures were better than traditional methods. Among them, the F1 measure was increased by 2.29% on average. [Limitations] Our new algorithm needs to be examined with datasets from Weibo or Twitter. [Conclusions] The proposed algorithm could effectively increase the accuracy of recommendation by defining and quantifying trust relationship among users. It improves the user experience of social network systems.

Keywords: Personalized Recommendation; UGC Tag; Tensor Decomposition; Multi-faceted Trust

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