Social Hybrid Recommendation Algorithm Based on Comprehensive Trust (Postprint)

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Date: 2018-10-11T00:00:00+00:00

Abstract

Recommendation systems are an important means to address the information overload problem. Existing trust network-based recommendation algorithms do not fully exploit user trust relationship information, which affects recommendation effectiveness. We propose a Comprehensive Evaluation of Trust (CETrust) model, which comprehensively considers factors such as direct trust and indirect trust among users. Combined with the feature attribute information of recommended items, it is integrated into a probabilistic matrix factorization model for recommendation. Experiments demonstrate that the newly proposed recommendation algorithm (H-CETrust) achieves higher recommendation accuracy than existing recommendation algorithms.

Full Text

Preamble

Social Hybrid Recommendation Algorithm Based on Comprehensive Trust

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Abstract: Recommendation systems are crucial tools for addressing information overload. Existing trust network-based recommendation algorithms fail to fully exploit user trust relationship information, limiting recommendation effectiveness. This paper proposes a Comprehensive Evaluation Trust (CETrust) model that incorporates both direct and indirect trust among users. By integrating item feature attribute information into a probabilistic matrix factorization framework, the proposed hybrid recommendation algorithm (H-CETrust) demonstrates superior recommendation accuracy compared to existing algorithms through experimental validation.

Keywords: recommendation system; trust network; trust assessment; item characteristics; probability matrix

1. Related Work

In the era of big data, the explosive growth of information forces users to spend excessive time locating relevant content. Recommendation systems have emerged as critical solutions to information overload. Collaborative filtering algorithms, known for their efficiency and convenience, are widely employed in recommendation systems. These algorithms identify users with similar interests to a target user and leverage their item ratings to predict the target user' s preferences. However, their accuracy is constrained by data sparsity and cold-start problems.

With the rapid development of social networks, researchers have proposed various algorithms for calculating trust between users. Golbeck introduced the TidalTrust algorithm, which performs a modified breadth-first search in trust networks to compute predicted ratings by aggregating ratings from trusted users along multiple paths. However, this method struggles to calculate trust values between non-adjacent users. Jamali et al. proposed SocialMF, a trust-based personalized recommendation algorithm that combines matrix factorization with trust propagation mechanisms, achieving high recommendation accuracy. Trust propagation has become a fundamental technique in trust-based social networks. Li et al. developed a social recommendation method integrating trust propagation and singular value decomposition, demonstrating effective and efficient quality improvements. Guo et al. introduced a trust-intensity-sensitive social recommendation algorithm that further enhances precision through reinforced trust relationships. Qin et al. proposed a collaborative filtering algorithm fusing user trust and emotional preferences, utilizing diverse rating resources and user similarity scores or trust values to overcome recommendation limitations. Zou et al. presented a personalized recommendation method combining tensor decomposition with user relationships in social network environments, applicable to rapidly evolving personalized recommendation scenarios with different trust levels for various friends. Hu et al. developed a recommendation algorithm integrating ratings and trust relationships, using friend trust matrices to refine user feature vectors and address feature construction and trust transmission challenges. Hu et al. also proposed an algorithm incorporating implicit trust relationships to solve explicit data sparsity issues and improve recommendation accuracy. Zhang et al. introduced a personalized recommendation algorithm combining trust relationships and temporal sequences, ensuring recommendation timeliness by comprehensively considering trust dynamics. Similarly, Li et al. proposed a social network recommendation algorithm integrating contextual information, leveraging user location and temporal data to uncover latent social relationships and improve recommendation precision.

While these social recommendation algorithms have achieved promising results, most focus solely on user perspectives while neglecting item correlations. Additionally, they rely on direct trust relationships while ignoring indirect trust, resulting in insufficient trust information and inability to resolve cold-start problems. This paper proposes a Comprehensive Evaluation Trust (CETrust) recommendation model that integrates probabilistic matrix factorization, direct and indirect trust relationships, and item correlation attributes. The hybrid recommendation algorithm based on comprehensive evaluation trust and items (H-CETrust) demonstrates improved recommendation accuracy on the Epinions dataset compared to traditional collaborative filtering algorithms.

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2. Trust Network

2.1 Trust Network Structure

This paper employs trust networks to represent user trust relationships and social recommendation environments. Trust networks can be categorized as binary trust networks or general trust networks. [Figure 1: see original paper] illustrates a binary trust network where directed edges represent trust relationships with a trust value of 1. [Figure 2: see original paper] shows a general trust network where nodes represent users and directed edges represent trust relationships with varying degrees.

A trust network can be defined as a graph structure G = U, T_U , where U = {u , u , ···, u } represents a set of users, and T_U = {(u, v) | u U, v T_u} represents a set of relationships. Each node in G corresponds to a user u_k (k 1,2,···,n), and each edge corresponds to a trust relationship. t_uv denotes the direct trust degree from user u to user v, where t_uv [0,1] with higher values indicating stronger trust. The set of users directly trusted by user u is denoted as T_u = {v U | t_uv [0,1]}. Let I = {i , i , ···, i_m} be a set of items, and R_ui represent the rating given by user u to item i. In the recommendation task, given user u U and item i I, the unknown rating is predicted as the estimated score.

2.2 Trust Propagation Calculation

In trust-based social networks, trust degrees are measured by real numbers within (0,1) representing trust relationships between target users and their neighbors. In trust-based recommendation models, user relationships refer to direct trust, while indirect trust relationships are not utilized during recommendation. As shown in [Figure 3: see original paper], where user u’ s direct trust in user v is 0.7 and user v’ s direct trust in user w is 0.5, the indirect trust value t_uw from user u to user w can be computed through trust transitivity.

Common methods for calculating trust propagation are given by equations (1)-(4), which yield t_uw values of 0.42, 0.6, 0.3, and 0 respectively. Different trust propagation methods may produce varying indirect trust degrees.

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3. H-CETrust Recommendation Algorithm

Global information is difficult to compute in existing personalized recommendation algorithms, and challenges persist in recommendation accuracy, real-time performance, and cold-start problems. This paper leverages trust relationships in social networks to comprehensively consider trust values between users and item ratings. Matrix factorization decomposes the trust relationship network among users to study latent user features behind trust relationships. A novel recommendation mechanism based on trust relationships improves the scalability of user trust models. By fusing item correlation attributes, the CETrust model is optimized. Experimental results on the Epinions public dataset demonstrate that the proposed H-CETrust recommendation algorithm ensures recommendation accuracy in complex social networks with strong scalability.

3.1 Basic Concepts of the CETrust Model

When purchasing products, users are primarily influenced by two factors: their need for the product and their trust in friends. In existing social networks, direct trust (explicit trust) relationships between adjacent users are easily obtained, while direct communication opportunities between non-adjacent users are rare. Trust relationships between non-adjacent users (implicit trust) cannot be directly acquired, yet such indirect trust relationships can improve recommendation algorithm accuracy and help solve cold-start problems. Indirect trust can be derived from existing trust relationships and trust transmission mechanisms.

Ma et al.' s RSTE model considers direct user trust relationships but ignores indirect trust relationships. This paper improves the RSTE model by comprehensively analyzing direct trust relationships and using trust transmission mechanisms to determine indirect user trust relationships. This mechanism identifies additional users trusted by existing users through indirect trust computation. Considering user preference similarity, inter-user similarity is calculated to comprehensively evaluate trust relationships.

3.2 Trust Computation in the CETrust Model

In social networks, indirect trust can be obtained through computation. Fu Min proposed recursive calculation methods for trust values by analyzing trust transmission and aggregation characteristics.

where a, u, and v represent users; t_a,u denotes the trust value between target user a and user u; v is a node on the shortest path from a to u; and V_T is a set of users on the shortest path from a to u whose trust values exceed a specified threshold. The similarity between users a and u can be obtained by calculating the Pearson correlation coefficient.

where sim(a,u) represents the similarity between users a and u. After obtaining user similarity, these two features are combined. Recommended neighbors with high similarity and trust values increase trustworthiness. The new trust value _au between user a and user u can be computed using equation (7).

3.3 CETrust Probabilistic Graph Model

[Figure 4: see original paper] illustrates the CETrust probabilistic graph model. CETrust uses probabilistic rating prediction by first executing a comprehensive trust evaluation algorithm to obtain a new trust matrix T' . As shown in the right frame of [Figure 4: see original paper], unlike matrix T, matrix T' includes both direct and indirect trust relationships. By integrating all trust relationships into the recommendation algorithm through a matrix model, the objective function is optimized using gradient descent. T(u) is the set of users trusted by user u, and |T(u)| is the number of users trusted by user u. Here, are d-dimensional latent feature matrices for users and items. If the user and item feature matrices follow zero-mean spherical Gaussian priors, the user preference degree for items can be expressed probabilistically. In this case, the posterior probability distribution combining latent feature matrices U and V is

where is the density function indicating that x follows a Gaussian distribution with mean and variance ^{2}; the function represents the logistic function. The logistic function ensures that values remain within [0,1]. is an indicator function equal to 1 if user u rated item i, and 0 otherwise. represents the trust value from user u to user k, obtainable through equation (5).

3.4 Optimizing the CETrust Model

The CETrust model recommends items more accurately from the user perspective but does not consider the correlation characteristics of recommended items. However, connections between recommended items are also important factors in user decision-making. To incorporate content characteristics between items, the algorithm is extended based on the CETrust method.

Let X_i = {F , F , ···, F_j, ···, F_n} denote the set of item feature attributes. Keywords or tags describe item content, where F_j represents the j-th feature of X_i. If F_j equals 1, X_i possesses that feature; otherwise, it does not. Consequently, all items can form a two-dimensional matrix regarding item keywords, as shown in .

TABLE:1 Item-Feature Matrix

	Feature F	Feature F	···	Feature F
Item x				
Item x				

	Feature F	Feature F	···	Feature F
...				
Item x				

Item correlation is calculated using equation (9).

where F__xi,j represents the j-th feature attribute of item x__i. If the feature exists, F__xi,j = 1; otherwise, it is 0. The magnitude of C__xi,xk represents the correlation strength between two items, where C__xi,xk [0,1]. C = {C__xi,xk} denotes an (M × M) item correlation matrix. Decomposing the feature matrix C yields low-dimensional latent feature relationship matrices. The posterior probability distribution of the item correlation matrix C can be expressed using the low-dimensional feature vectors V__i, V__j from the decomposed item matrix V.

where represents the Frobenius norm of the corresponding matrix, indicating the sum of squares of all matrix elements. To reduce algorithm complexity, __u = __v is assumed.

The exponential function represents the feature correlation between recommended items X__i and X__j. If C__xi,xj 0, the exponential function value is 1; otherwise, it is 0. To optimize the CETrust model and improve recommendation accuracy, shared latent feature spaces combine item feature correlations, inter-user social trust, and rating information to further enhance recommendation precision. The probabilistic model is shown in [Figure 5: see original paper].

FIGURE:5 H-CETrust Probabilistic Model

The log joint posterior probability of U and V can be further expressed as

where is the derivative of the logistic regression function g(x). Equations (13) and (14) are used to obtain partial derivatives of variable L.

The local minimum of the CETrust objective function can be found through gradient descent methods on U and V.

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4. Experiments

4.1 Dataset and Evaluation Metrics

This paper uses the Epinions dataset for experiments, a common benchmark for recommendation algorithms. Epinions.com, established in 1999, is a well-known review website where users submit product and movie reviews. Each member maintains a trust list representing inter-user trust relationships, where a trust value of 1 indicates trust and 0 indicates distrust. The original trust values require no computation. The Epinions dataset includes ratings from 51,670 users on 83,509 distinct items.

Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) measure the accuracy of rating predictions, defined as:

where R_ui represents the actual rating from user u to item i; represents the predicted rating; and N denotes the number of test samples. Lower MAE and RMSE values indicate higher estimation accuracy and better recommendation performance.

4.2 Experimental Parameter Influence

This section evaluates the impact of parameters _c and dimension d on the H-CETrust algorithm. The Epinions dataset is randomly split, with 80% used for training and 20% for testing. In recommendation systems, _c = 0 indicates reliance solely on user trust relationships, while _c $\rightarrow \infty$ indicates dependence only on item correlation relationships. Clearly, combining both user trust and item correlation yields optimal recommendation performance.

Parameters are selected by setting _u = _v = 0.1 to obtain improved results and determine optimal values. RMSE and MAE values are calculated using latent feature matrix dimension d = 20 to determine the _c parameter value. **TABLE:2** shows experimental results (d = 20).

TABLE:2 Experimental Results (d = 20)

The data in **TABLE:2** demonstrates that _c significantly impacts recommendation performance, indicating that comprehensive consideration of user trust and item correlation improves recommendation quality. When _c = 20, MAE and RMSE values are relatively low, yielding optimal algorithm performance. **TABLE:3** shows experimental results (_c = 20).

TABLE:3 Experimental Results (_c = 20)

TABLE:3 reveals that higher dimensions produce better recommendation results, with dimension 10 outperforming dimensions 2 and 5. This occurs because larger user and item feature matrices enable finer-grained categorization, improving algorithm performance. Therefore, _c is set to 20 and dimension d to 10 for comparative experiments.

4.3 Algorithm Performance Comparison

To evaluate H-CETrust performance, RMSE and MAE metrics compare the following algorithms:

a) **NMF** uses non-negative matrix factorization without additional information, relying only on the user-item rating matrix for recommendations.

b) **PMF** is a basic probabilistic matrix factorization algorithm using user-item rating matrix information to predict unknown ratings without considering user trust relationships.

c) **RSTE** is a recommendation algorithm based on ratings and user trust relationships, proposed by Ma et al. It integrates rating information and user trust into a basic probabilistic matrix factorization framework but does not consider trust transmission.

d) **TrustSeqMF** is a recommendation algorithm based on temporal information and trust relationships, proposed by Zhang et al.

H-CETrust is the proposed recommendation algorithm. Using an improved RSTE model, this method considers similarity between items and trust transmission, representing a model-based social network recommendation approach employing matrix factorization. It comprehensively incorporates direct and indirect trust between users, trust propagation, user similarity, and item correlation relationships. The test set proportions are selected as 20%, 50%, and 80%.

FIGURE:6 compares MAE values across algorithms, while **FIGURE:7** compares RMSE values. The results demonstrate that H-CETrust considers both user trust relationships and item correlations from dual perspectives. The improved model significantly enhances recommendation effectiveness, with the proposed algorithm outperforming other experimental algorithms under both MAE and RMSE evaluation metrics.

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5. Conclusion

This study aims to establish an appropriate trust model for recommendation systems. By investigating existing trust-based collaborative filtering methods and recommendation models, their advantages and disadvantages were identified. A novel recommendation model was proposed that integrates probabilistic matrix factorization, direct and indirect trust relationships, trust transmission mechanisms, inter-user similarity, and item correlation information. Experimental results on real-world datasets demonstrate that the proposed algorithm is more feasible than existing trust-based methods and effectively addresses cold-start problems for new users and items.

The limitation of this research stems from privacy concerns in social networks, which restrict available information. Distrust information is not provided in many social networks. Future research should explore integrating both trust and distrust information into recommendation models and further investigate the propagation mechanisms and impacts of trust and distrust information.

References

[1] Massa P, Avesani P. Trust-aware recommender systems [C]// Proceedings

of ACM Conference on Recommender Systems. New York: ACM Press, 2007: 17-24.

[2] Ma Hao, King I, Lyu M R. Learning to recommend with social trust ensemble [C]// Proc of the 32nd International ACM SIGIR Conference on Research and Development in Information Retrieval. New York: ACM Press, 2009: 203-210.

[3] Ma Hao, Zhou Dengyong, Liu Chao, et al. Recommender systems with social regularization [C]// Proc of the 4th ACM International Conference on Web Search and Data mining. New York: ACM Press, 2011: 287-296.

[4] Golbeck J A. Computing and applying trust in web-based social networks [D]. [S. l.]: University of Maryland College Park, 2005.

[5] Jamali M, Ester M. A matrix factorization technique with trust propagation for recommendation in social networks [C]// Proc of the 4th ACM Conference on Recommender Systems. New York: ACM Press, 2010: 135-142.

[6] Li Weijiang, Qi Jing, Yu Zhengtao, et al. A social recommendation method based on trust propagation and singular value decomposition [J]. Journal of Intelligent & Fuzzy Systems, 2017, 32(1): 807-816.

[7] Guo Lei, Ma Jun, Chen Zhumin. A social recommendation algorithm with intensity of trust relationship [J]. Journal of Computer Research and Development, 2013, 50(9): 1805-1813.

[8] Qin Jiwei, Zheng Qinghua, Tian Feng, et al. A collaborative filtering algorithm with fusion trust and user emotional preferences [J]. Journal of Software, 2013, 24(2): 61-72.

[9] Zou Benyou, Li Cuiping, Tan Liwen, et al. Social network recommendation based on user trust and tensor decomposition [J]. Chinese Journal of Software, 2014, 25(12): 2852-2864.

[10] Hu Yun, Li Hui, Shi Ye. Social recommendation algorithm based on scoring and trust relationship [J]. Journal of Computer Applications, 2017, 37(3): 791-795.

[11] Hu Huicheng, Chen Pinghua. A recommendation algorithm based on implicit trust relationship [J]. Journal of Guangdong University of Technology, 2017, 34(3): 43-48.

[12] Zhang Zhijun, Liu Hong. Social recommendation model combining trust propagation and sequential behaviors [J]. Applied Intelligence, 2015, 43(3): 1-13.

[13] Li Hui, Ma Xiaoping, Hu Yun, et al. Social network recommendation system integrating context information [J]. Journal of Intelligent Systems, 2015, 10(2): 293-300.

[14] Fu Min. A research on trust and distrust-based collaborative filtering recommendation model [D]. Qinhuangdao: Yanshan University, 2012.

[15] Ma Hao, Yang Haixuan, Lyu M R, et al. SoRec: social recommendation using probabilistic matrix factorization [C]// Proc of the 17th ACM Conference on Information and Knowledge Management. New York: ACM Press, 2008: 931-940.

[16] Lee D D, Seung H S. Learning the parts of objects by nonnegative matrix factorization [J]. Nature, 1999, 401(6755): 788-791.

[17] Koren Y, Bell R, Volinsky C. Matrix factorization techniques for recommender systems [J]. IEEE Computer, 2009, 42(8): 30-37.

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