Research Progress of Trust Evaluation

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***Abstract*—Trust evaluation is one of the most important issues in trust related research. How to evaluate the trust between two users is the main problem faced by many current recommendation systems and trust research. Currently in many applications, such as movie recommendation, spam detection, and online borrowing, evaluating trust among users in a trust social network (TSN) is a key issue. Therefore, this paper introduces the development process of trust evaluation in two aspects. The first is trust evaluation under different factors, such as user information and evidence. The second is trust evaluation based on different methods, such as neural networks and collaborative filtering methods. In the future, more factors can be combined with neural networks and reinforcement learning for trust assessment. For user privacy protection, blockchain technology can be combined to better encrypt user information, making the results more accurate and close to reality, and apply to more recommendation systems.**

***Keywords*—Trust social network; neural network; collaborative filtering; trust evaluation**

I. Introduction

Trust has many definitions in different disciplines and environments [1], [2]. In the book "Trust", the Polish sociologist Peter Stompka studied trust as a sociological theory and made the simplest and most general definition of trust, that is, trust is a gambling of beliving in the possible actions of others in the future. In psychology, trust is regarded as an individual's psychological state. In this state, based on positive expectations of the trustee's intentions or behavior, the trustee may be harmed [3], [4]. Trust in computer science is based on psychology and sociology, and the standard has been defined. The definition of trust tends to use probability to express the degree of trust.

Trust evaluation is one of the current social network security issues. With the popularization of the Internet, people can communicate and interact with different users through various social networks. Due to the complexity and uncertainty of trust, trust evaluation is required. The evaluation question represents whether users should trust the information put forward by other users in the social network [5]. Trust evaluation can make the recommendation system recommendation more accurate, make the network environment more secure, and trust evaluation has been applied to real life, including online lending, malicious website identification [6], social network analysis [7], [8], vehicle network [9] and actively make friends [10] and so on.

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The current trust evaluation research issues include how to calculate trust across different social networks, how to use the limited information of users for accurate trust evaluation, and what information is used as evidence to accurately predict the trust between two people. To solve problems across different fields is mainly to use transfer learning and extract common features. The current difficulties in trust evaluation include long algorithm time, inaccurate prediction of trust values across different fields, and large amount of dynamic update calculations. At present, Liu et al. [11] use the unsupervised domain-adapted asymmetric three training model of Kuniaki Saito et al., and use common and special features between the two social networks to train the classifier to predict the trust classification of one of the networks. In order to protect the privacy of users and consider as much evidence as possible, it is now necessary to use limited information to predict the trust value of users. Liliana Ardissono et al.'s [12] trust-based recommendation system adds evidence of trust based on publicly anonymous information, that is, the quality of individual contributions and multi-dimensional global reputation.

At present, trust evaluation is applied to various aspects. For example, there are many examples of combining with neural network. For instance, Hu [13] used BP neural network technology to construct a C2C e-commerce trust evaluation model from the perspective of buyers. Che [14] used genetic algorithm to optimize the BP neural network model and proved its application value to the construction of the credit system of my country's life insurance industry. Xu [15] established a customer trust evaluation model based on the BP neural network method and studied mobile e-commerce customer trust evaluation. Wang [16] combined Analytic Hierarchy Process (AHP) and trained Radical Basis Function (RBF) neural network to complete the trust evaluation of e-commerce transactions. Ouyang [17] used BP neural network to improve the credit rating system of Small and Medium Enterprises. At present, the most common is to integrate trust evaluation into the recommendation system. In the future, trust evaluation will be combined with the dynamic changes of trust, and trust evaluation will be more used in various social software, which is convenient for everyone.

II. Basic knowledge of trust assessment

There are many definitions of trust, which are introduced in the following three aspects: trust expression, trust source and trust evaluation.

A. Trust expression

Tong et al. [18] believed that the expression of trust can be divided into three types: the first is represented by logic, which regards trust as binary, namely trust and distrust, which can be represented by 1 and 0, and others divide it into trust, distrust, and unclearness, which are represented by 1, -1and 0 respectively. The second is the level expression, that is, trust is considered as a discrete interval value, generally there are two cases [-1, 1] and [0, 1]. In the former case, absolute distrust is considered to be -1, and dubious is considered to be 0 and absolute trust is 1. In the latter case, 0 is distrust and 1 is trust. The third is the probability expression, that is, the degree of trust a user has to another user, the greater the probability value, the higher trust value of a user in another user. A probability of 1 indicates complete trust, and a probability of 0 indicates that one user has no trust to another user at all. For example, the relationship $R =< u, v, p >$ indicates that the probability that user u trusts user v is p.

B. Source of trust

According to Sherchan et al. [19], we can know that the evaluation basis of trust evaluation can come from three aspects. The first aspect is attitude. Attitude represents the trustees opinion of the trustee, and it can be trust/like/positive or distrust/like/negative. The second aspect is experience. When the principal interacts with the trustee or conducts a transaction, the principal can evaluate the performance of the trustee. For example, in [20], satisfactory transactions and unsatisfactory transactions are used to measure trust. The third aspect is behavior. Trust can also be evaluated based on behavior [19]. In [21] and [22], the author used replies, forwarding, and forwarding behaviors to capture trust information.

Adali et al. [23] also use communication behavior to measure trust. In addition to these application-specific behaviors, we also consider similarity as one of the behaviors. Similarity measures the similarity of two users, for example, their buying behavior [24], [25], the common community they join in [26], the similarity of personal information [27], [28], etc.

C. Trust assessment

Trust is connected and transitive [29]. Two users who are not directly connected in the social network indicate that there is no interaction between the two. Take a small example, as shown in Figure 1. This is a small social network where user A and user B are directly connected. There is a trust value between them. Similarly, user B and user D are directly connected, and user A and user D are not directly connected. If you want to evaluate the trust between user A and user D, you need to combine various factors to predict and assessment. Through this example, we can understand that it is not easy to predict and evaluate the unknown trust of two people who have not interacted. Therefore, we need to use various methods, combine more factors, and use a large number of real data sets to test and adjust.

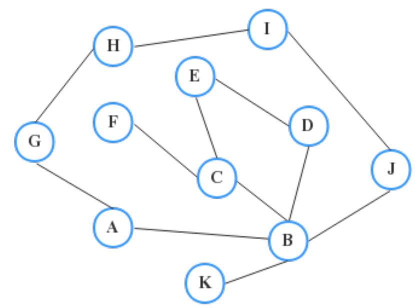

Fig. 1. Social Network

III. Trust evaluation based on different factors

In real life, to judge the degree of trust a user has in another user, you can get to know the person by chatting with him, so as to judge whether he is trustworthy or not. However, in virtual social networks, only some evidence can be used to judge the credibility of strange users, such as the number of mutual friends, hobbies, and evaluation among users. The following introduces some recent scholars efforts in this regard.

A. Trust evaluation based on user similarity

Studies have shown that people are more willing to trust people with similar backgrounds [30], [31], Wang et al. [5] used the similarity of information between users to cluster users to achieve the division of user groups, modify the relationship between users according to the results of user clusters and adjust the trust evaluation results. At the same time, they also considered malicious users. To ensure the robustness of the scheme, the trust detection scheme is added.

However, sometimes only a few ratings are used to calculate user similarity. Liu et al. [32] proposed a new user similarity model, which is suitable for the above situation. Its model takes into account the local context information of user ratings and user behavior. Using this method can effectively solve the problem of inaccurate trust evaluation caused by low user ratings and improve recommendation performance.

B. Subject-based trust assessment

Topic sensitivity analysis aims to solve the context-related problems in trust evaluation. For example, people use search engines to query related information. The search engines first look for the category topic they are in, and then find the most relevant content among the most similar topics and push them to users. Generally, trust evaluation is combined with topics to assess the similarity between users. It can be applied to the recommendation system to recommend by searching for users with similar interests.

Mao et al. [33] looked for a path of strong trust by comprehensively considering the user's theme of interest and the trust propagation ability of the corresponding node in the social network. The basic step is to prepare the two factors of the user's interest topic and the trust propagation ability of the corresponding node in the social network, then identify the strong trust path in the social network through three strategic breadth traversals that consider the combination of these two factors. Finally, the maximum, minimum, multiplication and average four strategies are combined into four strategies to summarize the trust rates of the source and target users.

Xu et al. [34] improved the trust evaluation framework proposed by Jiang and others [35], adding subject factors to evaluate the subject relevance between users.

The basic steps are as follows:

(1)Improve the integration process of trust evaluation under the network environment summarized by Jiang et al.. Add a topic extraction module on the basis of the information collection and trust evaluation module.

(2)Add user factors to the user topic model based on LLDA (Labeled LDA) to obtain the topic distribution of words and the topic distribution of users.

(3)Use the topic coverage function to calculate the topic coverage rate from the topic distribution obtained in the previous step.

They combined with topic coverage and used two traditional trust propagation methods (TrustRank and Appleseed) to extend them to be sensitive to different topics.

C. Evidence-based trust assessment

Dempster-Shaf theory was first proposed by Dempster [36] in the 1960s, then developed into its present form by his apprentice Shaf [37]. Unlike Bayesian theory, D-S evidence theory does not require prior knowledge probability,and it is widely used to deal with uncertain data, so combining D-S evidence theory with trust evaluation is a good processing method.

Wang et al. [38] used information flow prediction to assess the privacy leakage risk of assessed users. Then, both the user's willingness and the risk of privacy leakage were mapped to the trust evidence, and combined through the improved evidence combination rules of evidence theory. Inspired by the inaccuracy of trust, Feng et al. [39] proposed a novel Web user trust prediction method based on evidence theory, which used user ratings to infer the trust relationship between users, and each scoring score served as evidence.

IV. TRUST EVALUATION BASED ON DIFFERENT METHODS

Similarly, as mentioned earlier, judging whether a person is credible in real life can be judged by real-life contact. In virtual social networks, there are many prediction methods, such as neural networks and classic collaborative filtering. The following details the work in recent years.

A. Trust evaluation based on neural network

Generally, a social network can be represented by a graph $D = (V, E)$, where V is a collection of users, and the interaction between users is reflected on the links of edge E. Therefore, $E(D)$ is regarded as a set of edges between pairs, that is, $e(u, v) \in E(D)$. Here is an example of binary classification, that is, the user relationship is either 1 (trust) or 0 (untrust). To predict the relationship between two users, we need some factors to help us predict the user relationship. These factors can be user similarity, node clustering coefficient, edge clustering coefficient, personal contribution quality, global reputation and Pearson similarity, etc. These factors can be used as input. Taking the classic BP neural network as an example, as shown in Figure 2, it contains three layers from bottom to top, namely the input layer, the hidden layer, and the output layer. The input layer is a variety of judgment factors, and the hidden layer uses Relu function or sigmoid function, etc to process the judgment factors, and then outputs, calculates the error result, performs back propagation, adjusts the weight and deviation, reduces the error below the set threshold, and finally completes the training of the neural network.

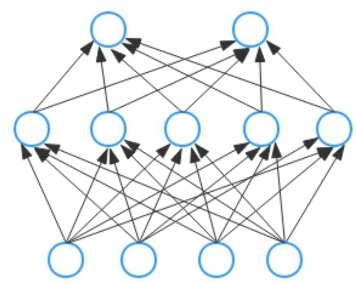

Fig. 2. Neural Network

Wang et al. [40] will study trust and distrust prediction based on the combination of Dempster-Shafer theory and neural network. First, by analyzing the predisposing factors of trust and distrust, namely homogeneity, status theory and emotional orientation. Then quantify the inducing factors of trust and distrust, use these characteristics as evidence, and build a prototype of evidence as the input node of the multilayer neural network. Finally, a framework for predicting trust and distrust is proposed. The framework uses a multilayer neural network to model the implementation process of Dempster-Shafer theory in different hidden layers to overcome the shortcomings of Dempster-Shafer theory without optimization methods.

For social networks where users are not directly connected, and there are multiple users between them, it is a big problem to evaluate the trust between these users. Liu and others [41] calculate multi-hop trust based on WalkNet and a given TSN, where WalkNet is a neural network architecture that can calculate user single-hop trust. NeuralWalk algorithm is used to "traverse" through TSN, and WalkNet is used alternately to calculate trust. NeuralWalk's algorithm is used to support multi-hop trust evaluation. NeuralWalk is an iterative algorithm, each iteration has two steps: training and inference. In the training step, the WalkNet is trained by minimizing the cross-entropy between the predicted trust level and the label. After training, it can learn the parameters that convert trust levels into opinions, as well as the parameters of discount and merge operators. In the inference step, NeuralWalk iteratively uses a well-trained WalkNet to perform single-hop trust inference on unknown trust relationships. Based on the single-hop trust inference results of each iteration, the algorithm will "traverse" the entire TSN in a breadth-first search (BFS) manner for multi-hop trust evaluation. NeuralWalk uses the neural network architecture WalkNet to capture the trust propagation and fusion in TSN. Previous work has shown that trust can indeed be propagated from one user to another, and several trust opinions of the trustee can be merged to obtain new trust opinions.

The trust evaluation methods mentioned above all involve some privacy of users. In real life, Considering user privacy protection, Ardissono et al.'s [12] trust-based recommendation system adds evidence of trust on the basis of publicly anonymous information, and enables them to be configured according to the data available in a given application domain. Factors such as personal contribution quality, multi-dimensional global reputation and other factors can be used as the basis for judging the relationship between two users.

In terms of trust evaluation, what most scholars currently do is to evaluate the trust between users of a network. There is very little work to evaluate the trust relationship of different networks, but in the current era of information exchange, It is necessary to predict the trust relationship of another network by analyzing the trust relationship of one network. Liu et al. [11] applied the unsupervised domain-adapted asymmetric three training model of Saito et al. [42] to trust evaluation. First, three classifiers were trained using the original samples, and then the trained N_1, N_2 were used. The two classifiers predict the target network, add pseudo-labels to the target unlabeled samples according to preset judgment conditions, and then use the pseudo-labeled samples and the original samples to train N_1, N_2 using algorithm 1, and then use algorithm 1 by considering the special features of the target network to training the third classifier N_t. Algorithm 1 is a process of neural network training. The difference from Saito et al. is that the input is the common and special features that have been summarized.

The advantage of using neural network to predict trust relationship is that it can make a more accurate prediction or classification of trust relationship based on past experience. Using neural network and transfer learning to predict trust relationship of different social networks needs further improvement. Future work further enhancements are needed, such as combining changes with dynamic changes in trust, improving the accuracy of trust classification, and combining more user factors while protecting user privacy. These are all tasks that need to be done in the future.

B. Trust evaluation based on collaborative filtering

Collaborative filtering has become one of the most commonly used methods to provide users with personalized services. The key of the method is to use the user item rating matrix to find similar users or items so that the system can display recommendations for users.

Davoudi and Chatterjee [43] proposed a method to predict the score of a personalized recommendation system based on similarity, centrality and social relationships. Compared with traditional collaborative filtering methods, the advantage of this mechanism is that it considers the value of social trust. The article uses the probability matrix decomposition method to predict the user score of the product based on the user item score matrix. Use level-based (ie, vector space similarity and Pearson correlation coefficient) and connection-based similarity measures to model similarity, centrality measure usage, feature vectors, Katz and PageRank centrality to quantify.

Resnick et al. [44] proposed GroupLens, which is a system for collaborative filtering of online news, which can help people find their favorite articles among a large number of available articles. This paper lays the foundation for future trust evaluation of matrix decomposition. Hill et al. [45] demonstrated a virtual community approach. Shardanand et al. [46] proposed a technique for making personalized recommendations to the user from any type of database based on the similarity between the users interest profile and the interest profile of other users. Based on the assumption that the matrix is local low-rank, a new low-rank matrix approximation is proposed. Lee [47] proposed a new matrix approximation model. In this model, they assume that the matrix is located in a low-order part, so that the observed matrix is expressed as a weighted sum of low-order matrices and the proposed algorithm LLORMA is highly feasible. Parallelized. Beutel et al. [48] proposed Additive Co-Clustering to Approximate Matrices Succinctly (ACCAMS), and obtained the theorem guarantee of matrix approximation through additive co-clustering. In order to improve the accuracy and scalability of recommendation, Chen and others [49] proposed a weighted ensemble matrix approximation method (WEMAREC), which divides the user item rating matrix into a set of sub-matrices, and then performs parallel processing on these sub-matrices To improve the scalability of the system. Wu et al. [50] proposed a new and scalable CCCF method to improve the performance of the collaborative filtering (CF) method through co-clustering of user items. Zhang et al. [51] proposed a new model for local low-rank matrix approximation, which uses a heuristic method to select anchor points. Liu et al. [52] proposed a non-parametric unified Bayesian graphical model for adaptive local low-rank matrix approximation (ALoMA). Meo [53] proposed the Peer-to-Peer Trust Prediction by Matrix Factorization (PTP-MF) algorithm, a method to predict the strength of trust and distrust relationships in online social networks (OSN).

Collaborative filtering is currently mainly used in various recommendation systems. According to user preferences, browsing records, evaluations and other information, the system predicts the users rating of the product through matrix decomposition, thereby performing product recommendations, and using collaborative filtering to recommend content that users may like. In future work, collaborative filtering can be used to more accurately predict the similarity of users to trust, filter more unnecessary information, and leave important information.

V. Conclusion

Here, we discussed the security issues of online social networks, namely trust ratings, and studied the trust evaluation of researchers on different factors and the trust evaluation using different methods in recent years. The steps of related research are introduced in detail. We thought that in future work, we could consider combining more factors with neural network and reinforcement learning for trust evaluation. The method can be improved in conjunction with the reward and punishment system. For user privacy protection, anonymous information can be used as much as possible without infringing on user privacy, or combining blockchain technology to better encrypt user information, making the results more accurate and close to reality.

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