

Retraction

Retracted: Network Data Mining Algorithm of Associated Users Based on Multi-Information Fusion

Security and Communication Networks

Received 25 July 2023; Accepted 25 July 2023; Published 26 July 2023

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] Y. Wang, S. Zhang, and S. Zhang, "Network Data Mining Algorithm of Associated Users Based on Multi-Information Fusion," *Security and Communication Networks*, vol. 2022, Article ID 9656986, 7 pages, 2022.

Research Article

Network Data Mining Algorithm of Associated Users Based on Multi-Information Fusion

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Received 5 June 2022; Revised 16 June 2022; Accepted 28 June 2022; Published 15 July 2022

Academic Editor: C. Venkatesan

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To explore how related users can optimize the network mining algorithm, the author proposes a related user mining algorithm based on the fusion of user attributes and user relationships. This method recommends key technical problems and solutions based on information represented by multi-information fusion and explores research on associated user network data mining algorithms. Research has shown that the associated user network data mining algorithm based on multi-information fusion is 65% higher than previous methods. AUMA-MRL has good performance under different network overlaps. Also, since the node embedding of the AUMA-MRL algorithm is obtained by neighborhood sampling, for new nodes in the network, the algorithm can quickly obtain the new node embedding, as well as the similarity vector between the new node and the rest of the nodes in the network, therefore, the associated users of newly added nodes in the network can be quickly mined, and the robustness of the mining algorithm of associated users in the network is enhanced. Compared with the existing classical algorithms, the recall rate of the proposed algorithm is increased by 17.5% on average, which can effectively mine the associated users in the network.

1. Introduction

With the rapid development of the Internet and computer technology, various network application services such as search engines, instant messaging, e-commerce, e-mail, etc. Have become important channels for people to obtain various network information, it can not only bring prosperity and development to the economy and great changes in society but also bring great convenience to many aspects of network users such as work and life [1]. The twenty-first century is the “information age, network age”. China Internet Network Information Center (CNNIC) defines Internet users as “Internet users refer to citizens who spend at least one hour on the Internet on average every week”, in other words, network users are people who use the network, people who use the network to obtain resources and exchange information in life, study, work, and other specific practical activities.

The mobile Internet is an extension of the traditional Internet, enabling people to access Internet resources using

mobile communication network technology. Its essence is that users must be in the center, so that users can get rid of the constraints of cables and the ability to freely access various web services in time and location. This “freedom” brings great challenges to the management and optimization of resources. In the context of large-scale users, since each user can access any mobile Internet resource at anytime and anywhere, it is affected by the comprehensive influence of user behavior preferences in the dimensions of time, space, and content, and there is bound to be a state in which some areas or periods of certain service traffic are intensive, while other areas or periods are sparse, the traffic-intensive areas are restricted by the total amount of communication resources, making it difficult to guarantee service quality, thus affecting user experience; The resource utilization rate in the sparse traffic area is low, resulting in a waste of resources [2].

In the big mobile big data environment, how to integrate existing technologies and resources, comprehensively, multidimensionally and three-dimensionally understand mobile Internet users’ online behavior from massive Internet

user record data, and design scientific and reasonable content predictions based on the acquired knowledge. Methods and resource optimization strategies are the key to addressing the challenges of the mobile Internet, as shown in Figure 1.

2. Literature Review

Although China's research on data mining is relatively late, it has a good momentum of development. Many subjects have been included in the national natural science foundation, the national high-tech research and development plan, and other key projects. The related work is mainly reflected in the in-depth study of algorithms and in-depth research on related theories, in the research of classification and recognition, attempts are made to establish theories related to set the classification to realize the processing of large-scale databases [3]. With the advent of the era of big data, in business, economics, and other fields, the technology of data mining has been applied more and achieved good results. For example, China's first big data scientific research achievement cloud service platform has been built; China Mobile has conducted mining and analysis of potential users of the HeReading business based on the big data platform, so as to improve the promotion effect of the HeReading business.

Network user behavior analysis requires knowledge of many disciplines, belongs to the research field of network behavior, and has high economic and scientific significance. The main subjects included are shown in Figure 2.

As far as the development of the United States is concerned, the practical application of data mining has become a hot spot in the American computer science community. The wide application of data mining technology, largely, promotes the development of various fields. Many companies in the United States attach great importance to the development and application of KDD, after a long period of development, they have developed many data mining software with excellent performance. In the field of general data mining, Weka has developed a comprehensive data mining platform. Data mining prototype system DB-Minerls is an interactive, multilevel mining system, and different levels of knowledge can be mined from the database. International academic journals have also opened up data mining technology columns, and many computer companies in the United States attach great importance to the development and application of data mining. The latest research on data mining technology in the United States is focused on the discovery of knowledge, focusing on the research on association rules and clustering methods [4].

The author proposes a multi-information related user mining algorithm AUMA-MRL, which is mainly divided into the following two steps: The node embedding method is used to learn the embedding of each node separately; The similarity vector of user pairs between the two networks to be fused is calculated according to the user node embedding. To verify the robustness of the proposed algorithm, the experiments were constructed with 33%, 45%, 60%, and 80% overlapped networks for comparative experiments to solve

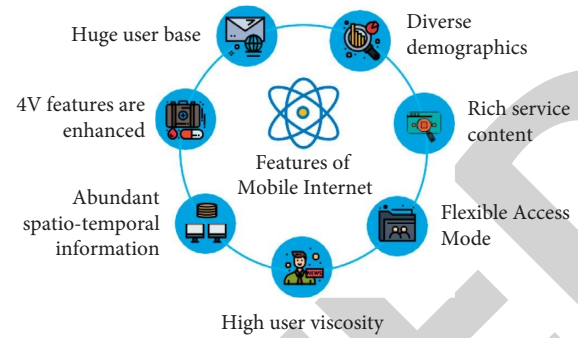


FIGURE 1: Mobile Internet features.

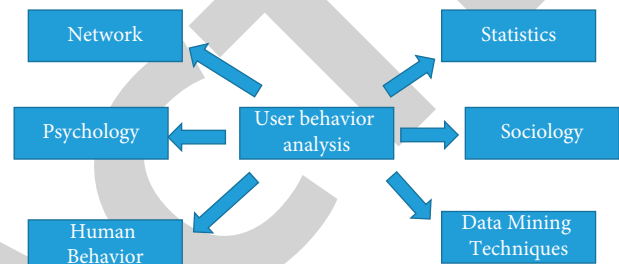


FIGURE 2: The influence of many disciplines on user behavior.

the optimization problem of the associated user network mining algorithm.

3. Methods

3.1. Associated User Mining Algorithm Integrating User Attributes and User Relationships. The goals of associated user mining are: Discover accurate and comprehensive associated users in two sparsely overlapping networks. Based on node attributes, neighborhood information, and network global structure information, the author proposes an associated user mining algorithm AUMA-MRL that integrates multi-information [5]. The algorithm is mainly divided into the following two steps:

- (1) Treat each user in the social network to be integrated as a node, and use the node embedding method to learn the embedding of each node, which integrates the user attributes and user relationship information of the network;
- (2) Calculate the similarity vector of the user pair between the two networks to be fused according to the user node embedding, and the similarity vector represents the similarity between users in different dimensions. Based on these similarity vectors, an associated user mining algorithm is constructed [6].

3.2. AUMA-MRL Algorithm. The core of the AUMA-MRL algorithm is to fuse multiple types of information contained in the network to be fused, embed it into a low-dimensional vector space, establish the connection between the two vector spaces through node similarity, and construct an associated node mining algorithm, therefore, how to obtain

accurate and effective node embedding is the key of this algorithm.

Generally, nodes in a social network with a large number of common neighbors have a higher similarity. The local topology of the network is obtained by sampling the neighborhood of network nodes. AUMA-MRL first uniformly samples the K -order neighborhood of the target node and sets the sampling window size as ω . The sampling process is described with the window size as a formula. The connection shown between the dotted line and the solid line in the figure constitutes the neighbor sequence of the target node, the solid line is the sampled node, and if the total number of neighbors of the target node is less than ω , the sampling can be repeated [7]. Each node in the network has an n -dimensional feature vector to describe the node attribute information (such as node text information, label information, etc.), and K fusion functions are trained through the deep neural network, as shown in formula (2). To learn the distribution of node attribute features of different depth neighborhoods, each layer of fusion function fuses the neighborhood information sampled by this layer and iteratively propagates the local neighborhood information of different sampling depths. Figure 3 is the network topology corresponding to Figure 4, which shows the fusion process of node neighborhood information, in which the dotted arrow is fusion1, and the solid arrow is fusion2, as shown in Figures 3 and 4.

$$\begin{aligned} \omega &= 2, \\ \forall K \in \{1, 2, \dots, K\}. \end{aligned} \quad (1)$$

We choose the pooling function to fuse the node neighborhood information, when the neighborhood depth of the target node v is k , its neighborhood information can be fused as shown in (2), according to this function, the vector of each neighbor node of the target node v can be independently propagated through the fully connected neural network, and finally, the neighbor information of v can be fused through the maximum pooling:

$$h_{N(v)}^k = \max(\{\sigma(W_{\text{pool}} h_u^{k-1} + b), \forall u \in N(v)\}). \quad (2)$$

The vector $h_{N(v)}^k$ obtained from the above neighborhood information fusion process is cascaded with the current vector representation h_u^{k-1} of v , and h_u^k is obtained through the nonlinear activation function σ , where h_u^k is the $k+1$ order neighborhood fusion, which provides the vector representation of the node. The above neighborhood information fusion process acquires a representation vector for each node in the network, this process saves the topology information of the node neighborhood through node neighborhood sampling and acquires the attribute information of the target node through neighborhood information fusion [8], as shown in the following equation:

$$z_v = h_u^k, \quad v \in V. \quad (3)$$

To obtain an embedding that effectively fuses user attributes and user relationships, so that nodes with similar attributes and structures have similar embedding

representations, use a graph-based loss function and gradient descent to learn the parameters in the fusion function. It assumes that neighboring nodes have similar embeddings, and discrete nodes have low-similar embeddings [9], as shown in the following equation:

$$L(z_v) = -\log(\sigma(z_v^T z_u)) - Q * E_{u_n \sim p_n(u)} \log(\sigma(-z_v^T z_u)). \quad (4)$$

Among them, node u appears in the random walk sequence starting from node v , P_n is the negative sampling distribution, Q is the number of negative samples, and z_v is the fusion representation generated by the features in the local neighborhood of node v .

Since the above node neighborhood information fusion process only samples the K -order neighborhood of the target node, and the sampling window is fixed, therefore, the local structure information of the neighborhood of the node is indirectly saved; However, this process does not save the global topology information of nodes in the network, that is, the complete user relationship. To fuse user attributes and relationships completely and effectively, the adjacency matrix A is introduced into the loss function [10].

Since the adjacency matrix A represents the relationship between nodes in the network, the matrix preserves the complete network structure information, that is, the user relationship. The adjacency matrix is defined as follows: If there is a link between node i and node j , as shown in (5), otherwise as in (6), by maximizing the correlation between the global relationship feature A_v of the node v and the neighborhood feature z_v , the user attributes and user relationship information are fused, as shown in (7), thereby, node embeddings that integrate user attributes and user relationships are obtained. Each row A_v in the adjacency matrix A represents the global relationship feature of node v [11].

$$A_{ij} = 1, \quad (5)$$

$$A_{ij} = 0, \quad (6)$$

$$\begin{aligned} L(z_v) &= -\log(\sigma(z_v^T z_u)) \\ &\quad - Q * E_{u_n \sim p_n(u)} \log(\sigma(-z_v^T z_u)) \\ &\quad - \text{corr}(f_1(A; \theta_1), f_2(z_v; \theta_2)). \end{aligned} \quad (7)$$

In formula (7), as shown in formula (8). The final node embedding can be obtained by solving the loss function. The embedding fuses the user's attribute information and user relationship information in the social network and represents this information as a low-dimensional dense vector, which provides a good feature basis for the associated user mining problem [10].

$$f(x) = \theta_x + b. \quad (8)$$

Due to the social relationship and attribute information of the same natural person, there are certain similarities in different social network platforms, therefore, the similarity of node pairs between networks is used to judge whether the

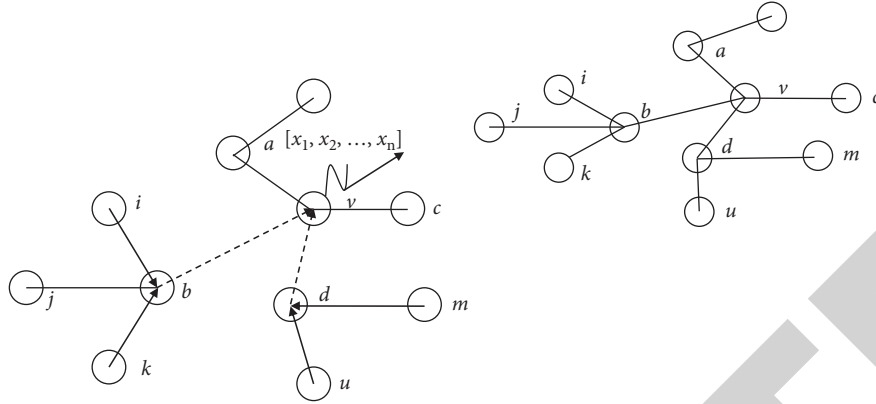


FIGURE 3: Sampling and fusion process of AUMA-MRL 2.

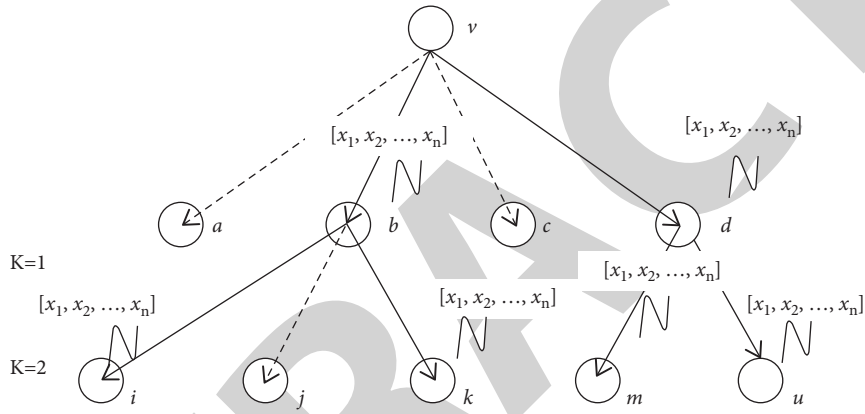


FIGURE 4: Sampling and fusion process of AUMA-MRL1.

node pairs are associated users [12]. The node embedding obtained above can directly measure the similarity between node pairs, the similarity calculation formula is shown in the following equation:

$$\text{Sim}_{ij} = \sqrt{(R_i^A - R_j^B)(R_i^A - R_j^B)^T}. \quad (9)$$

The similarity vector of nodes between networks is obtained by $R^A - R^B$ calculation, and the similarity between nodes is taken as one dimension in the similarity vector. Using the known association information of a small number of user accounts in the network as the nodes between the networks, the labels of the similarity vectors construct a model for the marked node pairs and perform parameter training, the associated user mining model is obtained, and the model is used to judge whether the unlabeled node pair is an associated user [13]. Given a set n , where n is the real labeled data $\{(x_{ij}, y_{ij})\}$ extracted from N_v , x_{ij} represents the D -dimensional similarity vector between user i and user j , as shown in (10), it indicates whether two users are the same natural person in the real world.

$$y_{ij} \in \{1, -1\}. \quad (10)$$

AUMA-MRL establishes a user pair association mining model f based on a support vector machine (SVM), which is used to judge whether the node pairs between the networks

to be fused belong to the same natural person, as shown in Equations (11)–(13):

$$f(x) = w^T x + b, \quad (11)$$

$$L_{(w,b)} = \frac{\gamma}{2} w^2 + C \sum \xi_{ij}, \quad (12)$$

$$\text{s.t. } y_{ij}(w^T x_{ij} + b) \geq 1 - \xi_{ij}, \xi_{ij} \geq 0. \quad (13)$$

Among them, the model parameters w and b can be obtained by minimizing the objective function in (13). The objective function $L_{(w,b)}$ is the standard structure loss minimization problem of binary classification, where C is the penalty parameter for misclassification, ξ_{ij} is the slack variable to ensure the nonlinear separability of the model, and b is the deviation of the data. The associated user mining problem is transformed into a binary classification model based on node similarity vectors [14]. Through the classification decision function $f(x)$, the node pairs in the network are divided into two types: Related users and nonrelated users, so as to realize the mining task of related users between different network platforms. The above process is shown in Figure 5, where R_A and R_B respectively represent the node embedding matrices of the two networks, and N_A and N_B respectively represent the number of nodes of the two networks.

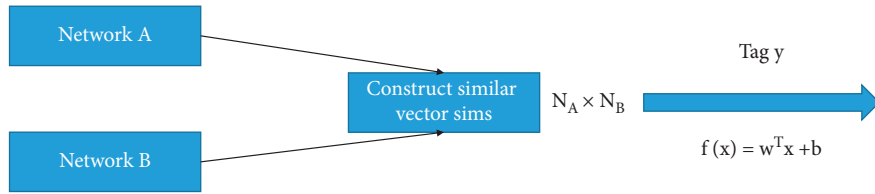


FIGURE 5: The associated user mining algorithm AUMA-MRL based on multi-information fusion representation learning.

The complete process of the AUMA-MRL algorithm is shown in (14) for a given set of networks to be fused, each node is traversed separately, and the neighborhood information of the nodes is sampled and fused to obtain the neighborhood feature z_v . Neighborhood feature Z and global feature A are weighted using parameters θ_1 and θ_2 to obtain the complete node embedding R . The similarity between nodes is calculated according to the embedding of two network nodes, and the training set of the model is constructed according to prior knowledge. To find the optimal parameters of the objective function, a model is built to perform associated user mining for all pairs of nodes across the network [15]:

$$\{G_A(V, E), G_B(V, E)\}. \quad (14)$$

4. Results' Analysis

4.1. Experiment. In order to verify the applicability and effectiveness of the AUMA-MRL algorithm in the associated user mining task, associated user mining experiments are carried out on three real public datasets. The statistics of the three datasets are listed in Table 1. PPI is the biological protein network, the network contains text information and node category information, and experiments use the associated user mining algorithm to perform protein retrieval tasks in protein networks [16]. Flickr is a well-known photo-sharing site whose users form relationships in social networks, and the website provides the user's tag information. Facebook data is collected from survey participants using the Facebook APP, and contains information on various attributes of users [17].

In the experiment, multiple sets of overlapping networks with overlapping degrees of 33%, 45%, 60%, and 80% were extracted from the three networks, respectively. The degree of network overlap is measured using $|X\Delta Y|/|X\cup Y|$, where X and Y represent the node sets of the two networks, respectively. Therefore, when the network has 1/2 of the same nodes, the node overlap is about 33%. In the experiment, according to the account association information provided by some users, we extract 20% of the node pairs from the internetwork node pairs to construct the experimental training set [18]. To evaluate the model reasonably, the NS algorithm and the Grh algorithm, which are currently better in mining associated users, are selected for comparison, the NS algorithm and the Grh algorithm select the node with a larger degree value as the seed node, that is, 10% * N nodes are selected from the top25% node degree values of the network as seed nodes, where N is the total number of

TABLE 1: Dataset information.

Data set	Number of nodes	Number of sides	Clustering coefficient
PPI	14755	22109	0.1772
Flickr	80513	5899882	0.1652
Facebook	4039	88234	0.6055

network nodes. The associated user mining results are first evaluated using precision and recall. When the network overlap is 60%, the recall rates of different algorithms for mining associated users in the three groups of networks to be fused are compared. It can be seen that the AUMA-MRL algorithm has achieved the best results on the three datasets, it is proved that the fusion of user attributes and user relationship information is more effective than only using user relationships for associated user mining, and the AUMA-MRL algorithm can effectively mine associated users in the network, in Table 2 [19].

To verify the robustness of the proposed algorithm, the experiments were constructed with 33%, 45%, 60%, and 80% overlapped networks for comparative experiments. Figure 6 compares the accuracy of the two algorithms in completing the associated user mining task under different network overlaps. It can be seen that the accuracy of the AUMA-MRL algorithm is higher than that of the NS algorithm. Due to the increase in network overlap, the node embeddings contain richer similar information, so the accuracy of associated users increases with the increase of network overlap [20]. Figure 7 shows the recall rates of the two algorithms under different network overlaps, the results show that the recall rate of the AUMA-MRL algorithm is slightly higher than that of the NS algorithm, and with the increase of the overlap, the recall rate continues to increase. The proportion of associated users in the network to be fused is lower than the proportion of unassociated users, and it has little effect on improving the recall rate of unassociated user pairs during prediction, so the recall rate is slightly lower than the precision [21], as shown in Figures 6 and 7.

From the above experimental results, it can be seen that the proposed associated user mining algorithm AUMA-MRL based on multi-information fusion representation learning has good performance under different network overlaps [22]. In addition, since the node embedding of the AUMA-MRL algorithm is obtained by neighborhood sampling, for new nodes in the network, this algorithm can quickly get the new node embedding and the similarity vector between the new node and other nodes in the

TABLE 2: Comparison of algorithm recall rate when overlap is 60%.

Algorithm	PPI	Flickr	Facebook
NS	0.3144	0.3250	0.2300
Grh	0.3997	0.1194	0.1157
AUMA - MRL	0.4195	0.3937	0.4291

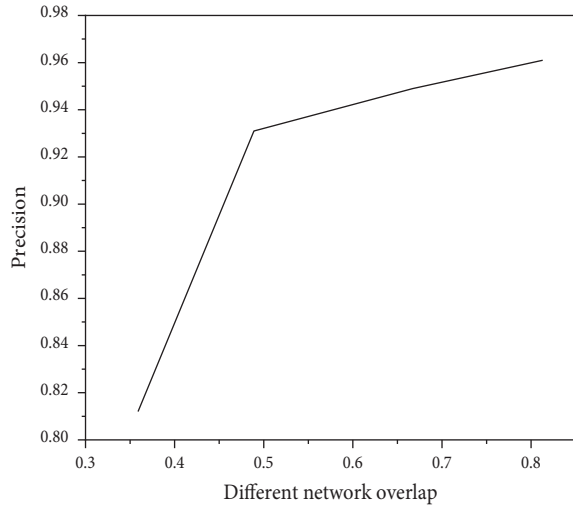


FIGURE 6: Comparison of accuracy under different network overlaps.

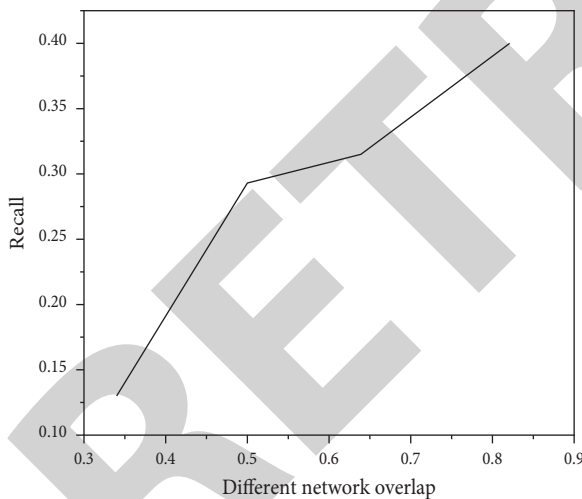


FIGURE 7: Comparison of recall rates under different network overlaps.

TABLE 3: Choose a different database.

Name database	Number of items	Number of transactions
Wenke	15	1000
Likc	15	3000
Gongkc	15	6000

network, therefore, it can quickly mine users associated with new nodes in the network and enhance the robustness of the network associated user mining algorithm, in Table 3 [23].

By choosing different databases, it is found that compared with the existing classical algorithms, the recall rate of the proposed algorithm is increased by 17.5% on average, and it can effectively mine the associated users in the network [24].

5. Conclusion

Based on the associated user mining algorithm AUMA-MRL based on multi-information fusion representation learning, the author integrates user attributes and user relationships through the network node embedding method and builds an associated user mining model. The model can avoid malicious user attacks and improve the precision and recall rate of the associated user mining model.

Due to a large amount of data in social networks and the similarity, sparsity, falsity, and inconsistency of user attributes, associated user mining methods for social network fusion face many challenges: (1) As the difficulty of acquiring prior information increases, how to accurately mine associated users with no prior or very little prior is an important research content in currently associated user mining; (1) The scale of today's social network users has reached tens of millions or even hundreds of millions, many existing associated user mining methods are no longer applicable due to computational complexity issues, how to mine associated users in social networks under massive data will be an important research direction.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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