International Journal of Computer Science and Information Technology

ISSN: 3005-9682 (Print), ISSN: 3005-7140 (Online) | Volume 3, Number 1, Year 2024

DOI: https://doi.org/10.62051/ijcsit.v3n1.14

Journal homepage: https://wepub.org/index.php/IJCSIT/index

Optimizing Opportunistic Routing between Communities Using Decision Trees and Apriori Algorithm

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ABSTRACT

This study proposes a novel data transmission framework aimed at optimizing node data transmission between different communities. We have designed an intelligent routing strategy based on node characteristics for situations where the source node and destination node have different communities. Through the decision tree algorithm, we trained a model to identify "messenger nodes" that are specifically responsible for cross community data transmission. In addition, the association rule model constructed using the apriori algorithm can calculate the probability of establishing a connection between the "messenger node" and the destination community node, thereby selecting the optimal path for data transmission. This method effectively reduces transmission delay and improves the efficiency and reliability of data transmission.

KEYWORDS

Decision tree; Apriori; Probability of meeting; Opportunistic routing

1. INTRODUCTION

Opportunity network [1-3] is a novel network topology that strongly supports 5G networks and big data environments, enabling end-to-end data transmission between nodes in unstable and discontinuous wireless networks. The opportunity network's transmission method based on "storage carry forward" [4-5] determines that data does not require any infrastructure support during transmission. In data transmission, nodes with data messages will randomly move to the communication area of other nodes, select suitable and reliable nodes from their neighboring nodes as relay nodes, and transmit data packets to the other party. If a node does not have a suitable transmission target during the transmission process, messages will occupy a large amount of cache, and data transmission is likely to wait for a long time, causing transmission delay. The unique data transmission method of opportunistic networks imposes higher requirements on the design and construction of routing algorithms, posing great challenges to the allocation and management of network resources such as cache, energy, and bandwidth. At the same time, it also brings more opportunities for data routing and transmission environments [6].

Early researchers proposed many solutions to the problem of opportunistic network node connectivity. Vahdat and Becker proposed a routing protocol based on flooding [7] technology, which widely propagates through flooding strategies. However, the widespread dissemination of messages results in high resource consumption and network overhead. The state of message transmission is closely related to the chance of encountering the target node. In order to reduce network overhead and determine a good relay node selection indicator, some researchers propose context aware, which calculates the probability of node encounters based on the node's encounter history. For example, Lindgren et al. proposed the PRoPHET [8] algorithm, which estimates the predictability of node delivery based on historical encounter situations. If a node successfully delivers a message to the destination node, the predictability of delivery increases; otherwise, the predictability of delivery decreases. However, this algorithm only considers the success of node message transmission and does not take into account social issues. Later, researchers addressed the selection of opportunistic routing relay nodes by considering the community to which the node belongs and node centrality. The Bubble Rap [9] algorithm evaluates the impact of community and centrality on forwarding, using centrality and community as the selection criteria for relay nodes, providing a new approach to opportunistic routing algorithms. In recent years, many papers have proposed other opportunistic routing algorithms that utilize community partitioning for message transmission. Zheng et al. [10] proposed an effective social relationship based forward transmission routing algorithm (EPTR). In this scheme, nodes with high relationship strength are selected to participate in the data forwarding process, so that data packets are transmitted towards the destination community in the direction of improving node forwarding ability. Yu et al. [11] established probabilistic encounter social relationships through the encounters brought about by node movements and proposed an opportunistic network routing strategy based on individual node communities. From the starting point of these papers, their purpose is to find a better method to determine the selection of relay nodes.

Compared with other routing forwarding algorithms, an effective routing forwarding algorithm has fewer hops in all successful message forwarding processes, resulting in nodes spending less time and energy during the forwarding process. How to select reliable relay nodes is a very important issue in routing and forwarding algorithms. Therefore, a chance routing mechanism based on association rule algorithm is proposed to address this issue. This article takes into account the unclear ownership of boundary points and uses them in the opportunistic routing transmission proposed in this paper. Under this mechanism, the source node and destination node are not in the same community, and a routing strategy for data transmission between communities is proposed. In the process of data transmission, if the mobile node does not have a suitable transmission target, messages will occupy a large amount of cache, and data transmission between communities is likely to wait for a long time, causing transmission delay. Therefore, in the process of selecting relay nodes, combined with the node's own attribute characteristics, a decision tree algorithm is used to train a "messenger node" recognition model, and messages are transmitted across communities through the use of "messenger nodes"; And use the Apriori algorithm to construct a relationship model and calculate the probability of establishing a connection between the destination community node and the messenger node. Select the appropriate "messenger node" based on the probability and ultimately deliver it to the destination node.

The main research contributions of this article are as follows:

(1) Based on the characteristics of the nodes themselves, a decision tree algorithm is used to train a "messenger node" recognition model, and cross community data transmission is achieved by utilizing the trained "messenger nodes".

(2) Using the Apriori algorithm to construct a relationship model between the destination community node and the messenger node, and calculating the probability of establishing a connection between the messenger node and the destination community node.

The rest of this article is organized as follows. Firstly, the second section introduces the relevant work. Then, the third section provides a detailed description of the system model. The fourth section provides a detailed description of the routing mechanism proposed in this study. Then, the fifth section provides a summary of this article.

2. RELATED WORK

The current proposed opportunistic network routing algorithms can be divided into two types. There are two types of routing algorithms: zero message routing algorithm and message assisted routing algorithm. Zero message routing algorithms include two types: direct transmission and Epidance. For direct transmission, the idea of this algorithm is that the source node always carries messages for mobile encounters until it encounters the destination node, and then the source node passes the message to the destination node. This transmission method has the fewest number of copies, which means it has the lowest network overhead, but it is time-consuming and has a low packet delivery rate. The Epidance algorithm [12] is designed to transmit data in a manner similar to infectious diseases, with extremely low packet delivery rates but exceptionally high network overhead. Both types of routing algorithms cannot achieve a balance between network overhead and resources.

In recent years, some researchers have proposed information assisted routing algorithms, which mainly rely on the efficiency value of nodes to select suitable relay nodes. At present, the node feature information mentioned in routing protocols mainly includes the node's historical behavior, location information, and social status. Wang et al. proposed an improved probabilistic routing algorithm (IPRA) [13], which combines the calculation of node contact probability using direct encounter and historical information of two hop neighbors to make message forwarding decisions. The HPR algorithm [14] calculates the probability of message transmission by combining two indicators: contact frequency and contact duration.

In recent years, some researchers have found that the mobility of nodes can be linked to user characteristics. When conducting opportunistic routing, they consider applying the user's mobility status to the transmission process of opportunistic routing [15]. These routing algorithms using social information [16-21] consider the user's social attributes to determine the transmission priority of nodes, calculate the activity of nodes in social relationships through different indicators, and then select appropriate relay nodes. The CMTR algorithm [20] proposes a social aware routing protocol based on cooperative mobility in a delay tolerant network environment, which calculates node centrality by considering the number of node encounters. Syed et al.[21] proposed a new routing method that utilizes both the spatial and temporal attributes of users, such as the probability of satisfying a specific location and the remaining contact time between two nodes, to select a better relay node.

In addition to using basic context awareness and derived social awareness based on context information to determine routing algorithms for relay nodes, some researchers have also analyzed the use of machine learning and studied many routing algorithms for opportunistic networks using machine learning in different scenarios [22-25]. Among them, Santos et al. proposed a routing mechanism called eGPDMI, which uses clustering techniques to group nodes based on energy levels and node interests. Improve message delivery rate while optimizing node energy consumption. The HiLSeR [25] algorithm utilizes the ability of machine learning to represent features, proposes a network topology segmentation algorithm based on node features, and applies grouping to intelligent transmission. The proposed HiLSeR scheme combines controlled parameterized flooding and decentralized transmission based on opportunistic sectors to achieve message routing.

Although information assisted routing can better balance network performance and resource consumption issues. However, the network overhead of these routes is still high. Therefore, the focus of this article is to study how to fully utilize node information to select suitable relay nodes, so as to have fewer hops in successful message forwarding and further reduce network overhead.

3. SYSTEM MODEL

3.1. Network Model

In the opportunity network, we define a network topology structure $G_t(V,E)$ with time attributes to model the opportunity network, where V is the node in the network, $V=\{v_1,v_2,...,v_n\}$, n is the total number of nodes in the network, E is the edge set reflecting the relationships between nodes in the network, $E=\left\{e_{v_1v_2},e_{v_1v_3},...,e_{v_iv_j}\right\}$, $m\neq n$, $e_{v_iv_j}$ represents the possibility of communication between node v_i and node v_j within a certain period of time.

3.2. Algorithm Model

Figure 1 shows the overall scheme of the algorithm in this study. The research mainly consists of three parts. Firstly, it determines whether a node is a "messenger node" based on its own attribute characteristics. Then, it participates in data transmission. Then, association rule algorithms are used to mine the relationship between the target community node and the "messenger node", select the appropriate one based on probability, and finally make routing decisions based on the node's importance and type.

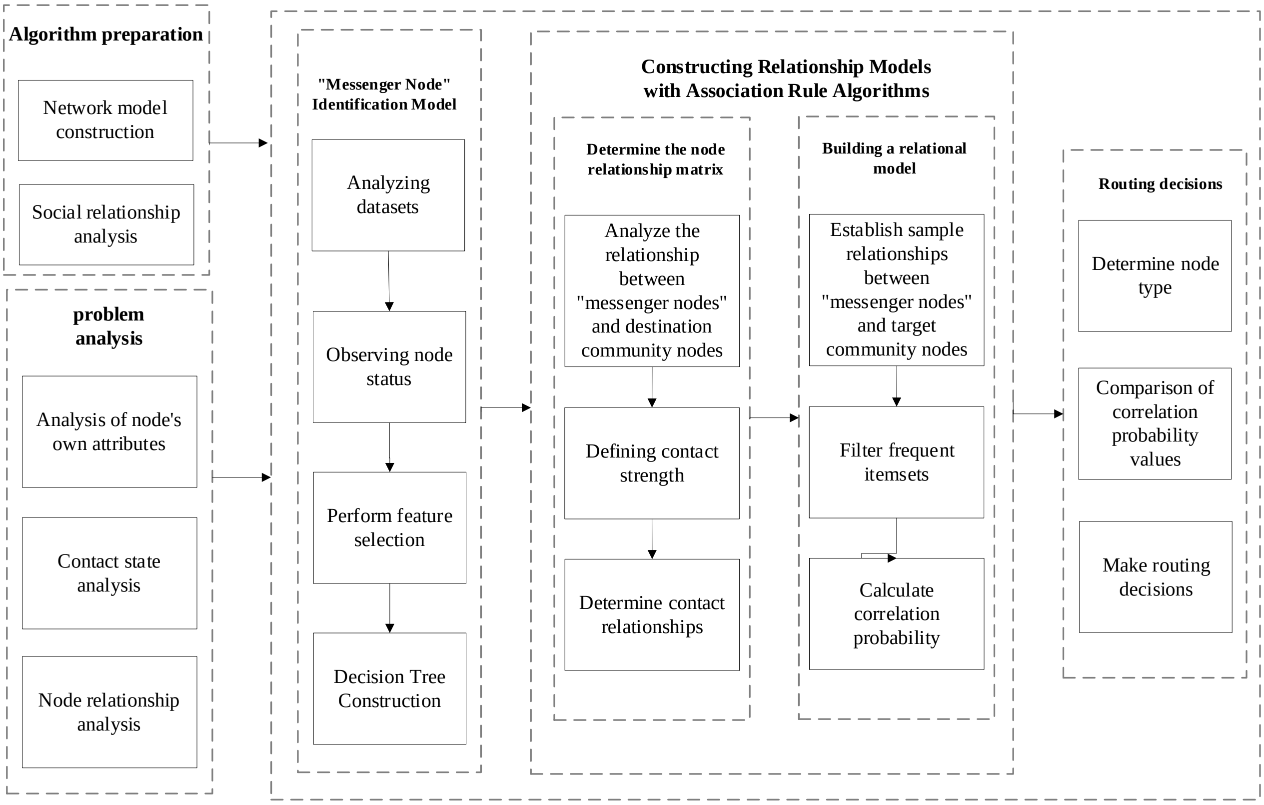

Figure 1. The overall algorithm routing design of this study

4. ROUTING PROTOCOL DESIGN

The transmission process of the routing algorithm in this article is shown in Figure 2. Node S is the source node with the purpose of successfully transmitting data to node D. In this routing transmission diagram, the transmission path represented by the red line needs to be implemented. During the transmission process, it is necessary to consider the attributes of the nodes themselves. The C4.5 decision tree algorithm is used to train the attributes of the nodes, and a "messenger node" recognition model is obtained to identify "messenger node M". Then, "messenger node M" is selected to carry data transmission, and a relationship model is constructed using the association rule algorithm to calculate the probability of "messenger node M" connecting with the destination node.

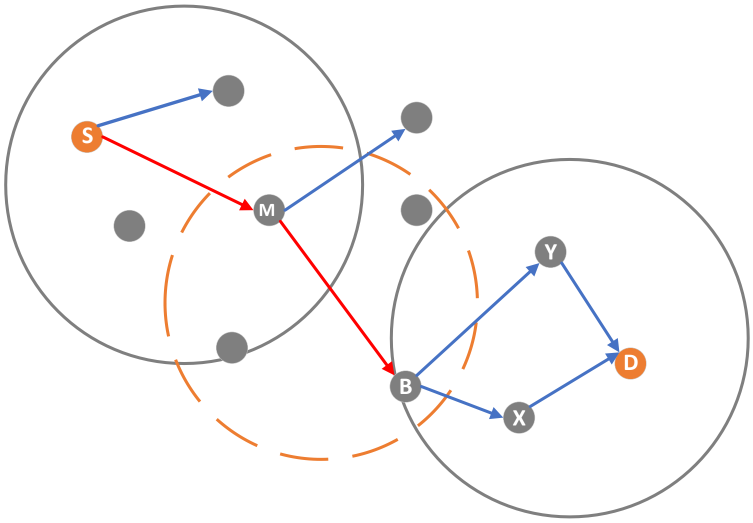

Figure 2. Routing transmission process

The first part of this chapter describes the implementation process of the "messenger node" identification model, the second part discusses how the association rule algorithm is applied to opportunistic routing, that is, calculating the probability of potential connections between the "messenger node" and the destination community node, and the third part sets the node importance and the entire process of routing decision-making.

4.1. "Messenger node" Identification Model

4.1.1. Feature selection

This article considers the communication capability, remaining cache, activity, and transmission load of nodes as the selected features in the C4.5 decision tree model.

1) Communication capability: If the connection state between node v_i and node v_j remains stable for a long period of time, it is considered that node v_i has strong communication capability during this period.

$$T_c(v_i) = \sum_{i=1}^{n} \left[T_{end}(i) - T_{start}(i) \right] \tag{1}$$

$$T_d(v_i) = \sum_{i=1}^{n} \left[T_{start}(i+1) - T_{end}(i) \right] \tag{2}$$

Among them, $T_c(v_i)$ represents the total time it takes for a node to meet and connect with other nodes, while $T_{end}(i)$ and $T_{start}(i)$ represent the end and start times of the node's i -th connection communication. $T_d(v_i)$ represents the total duration of node disconnection. n represents the total number of times a node has been connected during its lifespan.

So the communication capability of a node is defined as the following expression.

$$C_q(v_i) = \sum_{i=1}^{n} \left[(T_i - T_c(v_i)) - \frac{1}{n} T_d(v_i) \right]^2 \tag{3}$$

2) Node Remaining Cache: Refers to the remaining sequence length of a node. The larger the value, the less data packets the node carries, represented by $R_c(v_i)$.

3) Node activity: The activity of a node reflects its level of activity in the network. Represented by $A(v_i)$, the expression is as follows.

$$A(v_i) = \frac{\sum_{j=1}^{n} C_s(v_i, v_j)}{n-1}, i \neq j \tag{4}$$

Node activity represents the number of times node v_i contacts other nodes. As long as node v_i contacts other nodes once, $C_s(v_i, v_j)$ takes a value of 1, otherwise it takes a value of 0. The higher the $A(v_i)$ value, the greater the activity of the node and the greater the likelihood of contact with other nodes.

4) Transmission load: The current transmission load can be defined as the number of packets that have been forwarded before a certain moment. It represents the transmission load of a node at a specific point in time t. Represented by the expression $L(v_i)$.

4.1.2. Decision tree construction

By calculating and comparing the information gain rates of various attributes of nodes, select appropriate attribute features as the splitting attributes of the current node. The following is the calculation of the gain ratio of feature information for each node.

1) Training data preparation stage: Based on node encounter history, calculate the attribute features of each node.

2) The formula for calculating information entropy is shown below.

$$Entropy(S) = -\sum_{k=1}^{n} P(S_k)\log_2 P(S_k) \tag{5}$$

S represents the feature set, n represents the number of feature categories, and $P(S_k)$ represents the probability of each feature attribute appearing.

3) Information gain calculation: represents the degree to which the uncertainty of class Y information is reduced by knowing the information of a certain attribute feature X, represented by formula (10).

$$Gain(S,m) = Entropy(S) - \sum_{k=1}^{n} \frac{|S_k|}{|S|} Entropy(S_k) \tag{6}$$

m represents the feature attributes in the feature set.

4) Information gain ratio calculation: C4.5 uses the information gain ratio method to select attributes and split the feature set S. The attribute with the highest information gain ratio is the splitting attribute of the current node.

$$Gain\_ratio(S,m) = \frac{Gain(S,m)}{V(m)} \tag{7}$$

$$V(m) = -\sum_{k=1}^{n} \frac{|S_k|}{|S|} \log_2 \frac{|S_k|}{|S|} \tag{8}$$

Finally, based on the calculation results, select the attribute with the highest information gain ratio as the root node, and establish sub nodes according to the different values of this attribute; Generate new child nodes using the same method for each child node until the information gain ratio is small or there are no features to choose from, completing the construction of the decision tree.

5) Pruning stage: In the process of constructing the decision tree, in order to avoid branching anomalies caused by noisy and isolated points, a post pruning algorithm is used to prune the initial decision tree generated.

Use the remaining training samples to test the generated decision tree and adjust for incorrect branches; determine the final decision tree model by pruning and adding nodes to the decision tree.

4.2. Constructing Relationship Models With Association Rule Algorithms

4.2.1. Node relationships

Set a set of neighboring nodes $N_{set}(v_i)=\{v_j \mid D(v_i,v_j)<d\}$, where $D(v_i,v_j)$ represents the distance between node v_i and node v_j.

Set the total survival time of the node to $T=\{t_1,t_2,...,t_n\}$, divide the survival time of the node into n equal moments, and define the time intervals of different moments as τ. The contact situation of the node in these time intervals is:

$$E_\tau(v_i,v_j)=\begin{cases}1, v_j \in N_{set}(v_i)\\ 0, v_j \notin N_{set}(v_i)\end{cases} \tag{9}$$

When node v_j belongs to the set of neighboring nodes of node v_i, then the two nodes are in each other's communication area and can transmit data information to each other. The value of $E_\tau(v_i,v_j)$ is 1. When two nodes communicate with each other, the contact time $I_t(v_i,v_j)$ of the nodes is represented as follows.

$$I_t(v_i,v_j)=I_{t-1}(v_i,v_j)+\tau \tag{10}$$

When two nodes lose communication, the disconnection time $R_t(v_i,v_j)$ of the node is represented as follows.

$$R_t(v_i,v_j)=R_{t-1}(v_i,v_j)+\tau \tag{11}$$

The contact strength represents the ratio of the contact time and disconnection time of two nodes at time t. Expressed by the formula as follows, and $S_t(v_i,v_j)=S_t(v_j,v_i)$.

$$S_t(v_i,v_j)=\frac{I_t(v_i,v_j)}{R_t(v_i,v_j)} \tag{12}$$

The average contact strength represents the average contact strength between node v_i and neighboring node v_j at time t.

$$S_t^{average}(v_i,v_j)=\frac{\sum_{v_j\in N_{set}(v_i)} S_t(v_i,v_j)}{|N_{set}(v_i)|} \tag{13}$$

$|N_{set}(v_i)|$ represents the number of neighboring nodes of node v_i at time t.

4.2.2. Association rule algorithm for mining node relationships

Calculate the average contact strength between the "messenger node" and the destination community node based on the proposed concepts of node contact, and establish an n-dimensional node relationship matrix A based on the average contact strength of the nodes.

$$A = \begin{pmatrix} a_{v_1} & a_{v_2 v_1} & \cdots & a_{v_n v_1} \\ a_{v_1 v_2} & a_{v_2} & \cdots & a_{v_n v_2} \\ \vdots & \vdots & a_{v_m} & \vdots \\ a_{v_n v_1} & a_{v_n v_2} & \cdots & a_{v_n} \end{pmatrix} \tag{14}$$

In matrix A, the diagonal, $a_{v_1}, a_{v_2}, \ldots, a_{v_n}$ represents the average contact strength of node v_i predicted and calculated at time t. For the position in the j-th row and i-th column of the matrix, it is represented as the contact relationship $a_{v_i v_j}$ between node v_i and node v_j. When the contact strength between node v_i and v_j is greater than the average contact strength, it indicates that there is a certain communication relationship between the two nodes, and $a_{v_i v_j}$ takes a value of 1. Otherwise, it takes a value of 0. And $a_{v_i v_j} \neq a_{v_j v_i}$. The expression is as follows.

$$a_{v_i v_j} = \begin{cases} 1, S_t(v_i, v_j) > S_t^{average}(v_i, v_j) \\ 0, S_t(v_i, v_j) < S_t^{average}(v_i, v_j) \end{cases} \tag{15}$$

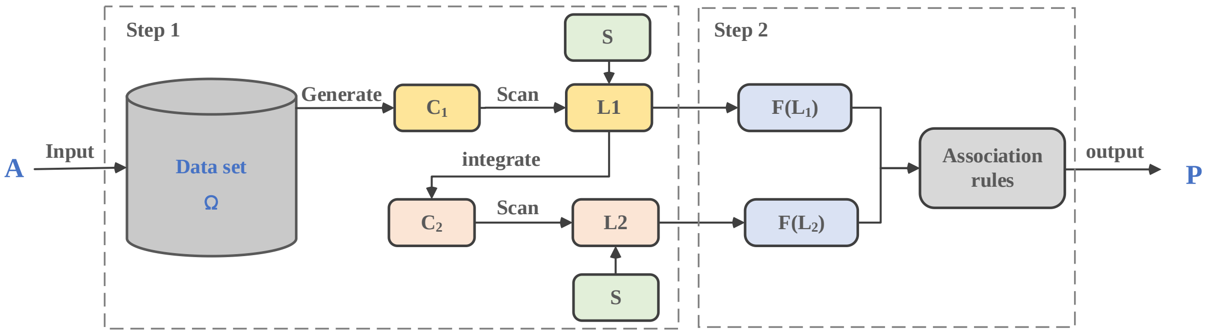

Figure 3. Node Relationship Model Based on Apriori Algorithm

The above formula introduces the node relationship matrix A based on the average contact strength of nodes. It can be found that the strength of the relationship between nodes can be determined based on the node relationship matrix A. Using the node relationship matrix A as the input for the association rule algorithm model, the potential relationship between the "messenger node" and the destination community node is mined by using the association rule algorithm. The association rule algorithm discovers potential relationship models in two steps, as shown in Figure 3. The first step is to store the node relationship matrix A as the input of the model in the node relationship sample set. Then, based on the sample set, a candidate single node set C_1 is generated, and C_2 is obtained by freely combining L_1. After scanning C_1 and C_2, frequent single node sets L_1 and frequent two item sets L_2 are obtained. The frequency of itemsets L_1 and L_2 is calculated based on the scanning process. The second step is to calculate the potential relationship probability between nodes by scanning the frequency of the itemset obtained. Then, based on the probability value, determine the appropriate "messenger node" that this study wants to choose. The specific algorithm explanation is as follows.

Step 1: Determine the frequency of the itemset. Assuming at time t that the frequent itemset is set to L, the frequency of itemset L is defined as follows.

$$F_t(L)=\sum_{i=1}^{n}F(L,v_k) \tag{16}$$

Among them, $F(L,v_k)$ represents the contact relationship between nodes in L and nodes v_k in the network. The frequent itemset L includes the frequent monomial set L_1 and the frequent binomial set L_2. Assuming that the nodes contained in itemset L_1 are $\{v_i\}$, when $L=L_1$, then $F(L,v_k)=F(L_1,v_k)$, the value of $F(L_1,v_k)$ is as follows.

$$F(L_1,v_k)=\begin{cases}1, C(v_k,v_i)=1\\0, C(v_k,v_i)=0\end{cases} \tag{17}$$

Among them, $C(v_k,v_i)$ represents the degree of relationship between L_1 and network node v_k, with a certain relationship value of 1, otherwise it is 0. And $v_k \neq v_i$. When $L=L_2$, then $F(L,v_k)=F(L_2,v_k)$. Assuming that the nodes included in itemset L_2 are $\{v_i,v_j\}$ and $v_k \neq v_i, v_k \neq v_j$, $F(L_2,v_k)$ is represented as follows.

$$F(L_2,v_k)=\begin{cases}1, C(v_k,v_i)=1, C(v_k,v_j)=1\\ \quad 0, \qquad\qquad \text{other}\end{cases} \tag{18}$$

After calculating the frequent itemsets, the Scan process is used to filter the itemsets, determine the frequency of the single and two itemsets, set the minimum support S, and select frequencies greater than the minimum support S.

Step 2: Calculate the probability of establishing connections between nodes. Assuming a set of two terms $\{v_i,v_j\}\in L_2$, the possibility of establishing a potential relationship between node v_i and v_j is expressed by the following formula.

$$P_t(v_i,v_j)=\frac{F_t(v_i,v_j)}{F_t(v_i)} \tag{19}$$

Among them, $F_t(v_i,v_j)$ represents the frequency of the two itemsets $\{v_i,v_j\}$ in L_2, and $F_t(v_i)$ represents the frequency of the single itemset $\{v_i\}$ in L_1. $P_t(v_i,v_j)\neq P_t(v_j,v_i)$.

4.3. Routing Decision Process

In our proposed data transmission framework, we consider the possibility that the source and destination nodes may be located in different communities. In order to optimize the efficiency of data transmission between communities, we have designed a routing strategy based on node characteristics. In actual transmission, if a mobile node does not find a suitable next hop target, it will cause messages to stagnate between nodes for a long time, occupy too much cache space, and increase transmission delay. To solve this problem, we developed a model for identifying "messenger nodes" using decision tree algorithm, taking into account the attribute characteristics of the nodes. These "messenger nodes" are responsible for transmitting data from one community to another. At the same time, association rule algorithms such as Apriori algorithm were also applied to construct a prediction model that can predict the possibility of establishing a connection between the destination community's nodes and the "messenger nodes". Select the most suitable "messenger node" based on the size of this probability value to ensure efficient data transmission to the destination node. This method not only improves the efficiency of cross community transmission, but also reduces the delay caused by waiting.

5. CONCLUSION

This article proposes an innovative cross community data transmission framework, which successfully trains a model that can recognize "messenger nodes" by combining decision tree algorithm and association rule algorithm. These "messenger nodes" can effectively achieve data transmission between different communities, significantly improving transmission efficiency and reducing latency. In addition, our method also has high implementability as it relies on existing algorithms and technologies that have been validated and have been applied in multiple fields.

We plan to conduct experimental verification in a real network environment to further evaluate the performance and reliability of our model. We believe that through experimental feedback, the model can be optimized to better adapt to dynamic network conditions. Ultimately, we hope that this research can provide strong theoretical support and practical guidance for achieving efficient and reliable data transmission between communities.

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