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Simulation of Communication Paths with Social Network Analysis as the Core and CAD Collaborative Visualization

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Abstract. Understanding the communication path mechanism in social networks and predicting and simulating the dissemination path of information has important practical value in many fields, such as marketing, public communication paths, and crisis management. This article aims to explore the mechanism and path of communication paths in complex social networks by integrating social network analysis, dissemination path simulation, and computer-aided design (CAD) collaborative visualization techniques and methods. The article first elaborates on the importance of social networks in today's communication paths, as well as the value of social network analysis in revealing key nodes, group dynamics, and information flow patterns. Then, it introduces the role of dissemination path simulation in predicting the speed and influence of information diffusion. The article also emphasizes the application of CAD technology in social network visualization, as well as its advantages in improving the understandability of network structure. By integrating these techniques and methods, this article hopes to provide new perspectives for the research and application of communication paths and to manage information resources in social networks more effectively.

Keywords: Social Network Analysis; Communication Paths Mechanism; CAD; Visualization
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1 INTRODUCTION

In today's highly interconnected world, social networks have become the core platform for communication paths, concept exchange, and diffusion of social influence. Whether through the hot search on Weibo, sharing in friends circle, or discussion in the community, social networks virtually shape our cognition and behavior. In this process, users particularly favour the forwarding of visual information because it can convey information content more intuitively and vividly. The application of CAD collaborative visualization technology provides strong support for the visualization of information-forwarding processes in social media. CAD collaborative visualization technology combines the advantages of computer-aided design (CAD) and visualization technology, enabling collaborative operation and display of visualization information such as 3D models, graphics, and images. In social media, Chen et al. [1] analyzed CAD collaborative visualization technology to gain a more intuitive understanding of the forwarding path, propagation speed, and impact range of information. Through CAD collaborative visualization technology, it clearly displays the forwarding path of visualized information on social media. By visualizing graphics and animations, track the transmission process of information from the original publisher to the final receiver, and observe the flow and diffusion of information between different nodes. Therefore, understanding the communication paths mechanism in social networks and predicting and simulating the communication paths path is of great practical value to many fields such as marketing, public communication paths and crisis management.

When conducting 3D design, attention is often paid to the structure, shape, and functionality of the model. Generating text descriptions can express these features in the form of text, enabling designers to better understand and describe the design intent. Generating text descriptions also helps to enhance the visualization and interactivity of feature-based 3D collaborative design. Through textual descriptions, Cheng et al. [2] effectively communicate with other team members or clients to ensure accurate communication and a common understanding of design concepts. Through textual descriptions, designers can combine the features of models with various media forms such as text, images, and animations to create more vivid and intuitive design displays. This visual expression not only helps designers better understand the design intent but also provides customers with more intuitive and easy-to-understand design solutions. Social network analysis can systematically describe the attributes of network nodes, the relationship between nodes and the structural characteristics of the whole network by using tools such as graph theory and complex network theory. In the digital age, social media has become an indispensable part of people's daily lives, and its influence has gradually penetrated into academic and educational fields. Especially in the process of collaborative design, students' use of social media not only changes traditional communication methods but also promotes innovative development of communication path simulation and CAD collaboration. In traditional collaborative design, students often need to communicate through face-to-face meetings, emails, or phone calls, which are not only limited by time and space but also often have unsatisfactory communication effects. CAD collaborative design refers to the process of using computer-aided design software for multi-person collaborative design. The combination of social media and CAD software enables students to collaborate more efficiently in design [3].

Dang et al. [4] studied the resource and power resource allocation problem of D2D communication devices based on social trust. Using social trust, provide the optimal energy efficiency relay device allocation algorithm for social perception. This algorithm uses a closed triplet model to mine hidden social trust relationships among mobile users, ensuring that more users are willing to join D2D collaborative communication. Meanwhile, the given algorithm jointly considers social and physical network constraints to determine the optimal relay device. Furthermore, based on game theory, the optimization problem is studied to reduce energy consumption and interference. In the game, social distance is used as a distributed penalty coefficient to control the transmission power of D2D communication. Simulation-based on actual social network statistics shows that the given algorithm can achieve significant performance gains compared to other relay device allocation algorithms. Communication paths are based on social network analysis and simulate the information propagation process in the network through mathematical modelling and calculation experiments. It can predict the diffusion speed, scope and influence of information under different network structures, and help decision-makers to formulate more effective communication paths strategies. However, communication paths face many challenges, such as the complexity of the network, the heterogeneity of node behaviour, the uncertainty of communication paths, etc., which requires that the simulation algorithm not only has a solid theoretical foundation but also has enough flexibility and scalability to adapt to different network environments and application scenarios. CAD collaborative visualization is a method that utilizes computer technology to simulate and optimize product design and manufacturing processes. It enables designers and engineers to understand and improve products more intuitively and efficiently. A mobile botnet is a network composed of a large number of mobile devices controlled by malicious software, which can engage in various illegal activities without being detected by users. Faghani et al. [5] utilize these controlled mobile devices to perform various social tasks, such as publishing information, collecting data, etc. This can not only improve the intelligence level of social networks but also bring users a more convenient and efficient social experience. In order to effectively identify and curb the spread of false information, CAD collaborative visualization technology for false information detection with social network analysis as the core has emerged. This technology provides strong support for the detection of false information by combining social network analysis and CAD collaborative visualization.

Guo et al. [6] studied the allocation of D2D communication equipment resources, channels, and power resources based on content preference. Taking into account both social and physical networks, provide an optimized D2D device pair matching and channel and power resource allocation algorithm for content preference. The probability of users selecting similar content for process modelling is used as a constraint and weighting factor to represent the impact of social network characteristics on D2D pair matching and resource allocation, respectively. In downlink cellular resource allocation, consider the Quality of Service (QoS) requirements of D2D pairs and cellular users. Establish a mixed integer nonlinear programming problem for resource allocation to maximize the total weighted data rate. And use a one-to-one stable matching algorithm to obtain optimized resource allocation results. Furthermore, the stability, optimality, and complexity of the given D2D matching and channel resource allocation algorithms were verified. The simulation results show that the given algorithm can significantly improve the matching success rate and data rate of D2D communication. Jafari et al. [7] studied the satisfaction-based visual allocation of communication channel resources and power resources in social networks. Based on the content preference model of social networks, an iterative resource allocation algorithm is proposed for joint satisfactory channel resource allocation and power resource allocation. The goal is to ensure QoS and maximize the weighted data rate of the total D2D. Nodes in the model can represent users or groups, while edges can represent social relationships between users or the communication Paths of topics.

Through the CAD system, we can display the complex social network data and the simulation results of communication paths in an intuitive and easy-to-understand way, helping analysts and decision makers to grasp the information communication situation and the changes in network structure more quickly. Integrating the technologies and methods of social network analysis, communication paths and CAD collaborative visualization, is expected to open a brand-new perspective for the research and application of communication paths, better understand the law of communication paths in complex networks, and thus manage information resources in social networks more effectively.

Highlights:

⊖ This article innovatively combines social network analysis with CAD technology, which provides a brand-new visualization means for communication paths.

⊜ This article not only deeply discusses the theoretical framework of social network analysis but also verifies its practical application effect in communication paths through experiments.

⊛ Using the powerful function of the CAD system, this study realized the three-dimensional dynamic visualization of social network structure and communication path.

④ Aiming at the complexity of communication paths, this article puts forward an optimization algorithm and proves its flexibility in different network environments through case analysis.

This article aims to explore the application of social network analysis and CAD collaborative visualization in communication paths. First, it reviews the basic theory and common methods of social network analysis, as well as the algorithm and model of communication paths. Secondly, it discusses how to effectively integrate social network data with CAD systems to realize three-dimensional reconstruction of network structure and dynamic simulation of communication path. Finally, the feasibility of this combination method is assessed through case analysis and experimental verification. It is expected that this research will not only promote the theoretical development of social network analysis and communication paths but also provide new ideas for the application practice in related fields.

2 RELATED WORK

Multi-mode feature secure social network communication refers to the use of multiple features and patterns in social networks to protect communication security. These features may include user identity information, behaviour patterns, network topology, etc., while patterns may involve data encryption, identity authentication, access control, etc.

Maximizing time sensitive influence based on topics in online social networks is a complex problem involving multiple disciplines, which combines key elements such as social network analysis, communication paths models, time sensitive algorithms, and topic specificity. In recent years, with the popularization of online social networks and the development of big data technology, research results in this field have become increasingly abundant. Min et al. [8] analyzed the results of maximizing time sensitive influence based on topics in online social networks. Sivasubramaniam and Chandrasekar [9] analyzed requirements in terms of functional requirements, non-functional requirements, design constraints, and other aspects. Afterwards, research and analysis were conducted on these requirements, and the final implementation method and proposed technical foundation were determined. It has completed the research and implementation of the overall architecture of social network visualization analysis tools. A hierarchical architecture solution has been proposed. After completing the component selection for visualized data presentation, a solution suitable for the actual situation of this project was selected from multiple solutions through comparison. Based on this, the design and implementation of the visualization part of the prototype system were completed. We analyzed and studied the communication methods between the rich client and server, determined a reasonable data transmission and information exchange method, and ultimately implemented the communication mechanism. With the advent of the information explosion era, the scale of data centre networks is constantly expanding, and server failures have become an inevitable occurrence. Therefore, ensuring reliable communication between servers in the data centre network is of great significance. The data centre network HSDC is constructed based on the famous network hypercube topology, retaining many excellent properties of hypercube networks, such as regularity and point symmetry. In addition, the data centre network HSDC also has advantages that hypercube networks do not have, such as excellent performance in incremental scalability. As a highly scalable data centre network, studying the reliable communication performance of HSDC has important theoretical and practical significance [10]. Tseng and Son [11] obtained their logic diagram by making the switches in HSDC transparent. Among them, the servers and their links in HSDC constitute the node set and edge set of H, respectively, and $n \geq 2$. Then, for the first time, this article studies the connectivity, fault-tolerant unicast path, disjoint path, Hamiltonian properties, and fault-tolerant Hamiltonian properties of H, in order to measure the reliable communication performance of HSDC. Connectivity is an important indicator for measuring the reliable communication performance of a network. The greater the connectivity of a network, the stronger its fault tolerance and reliable communication capability. In addition, connectivity is the foundation of subsequent research in this article. When the number of faulty nodes in the network is less than the connectivity, there is at least one faultless path between any two different faultless nodes in the network. The fault-tolerant unicast path ensures reliable data transmission between any two fault-free nodes in the network. Non-intersecting paths can reduce the packet loss rate during data transmission through parallel transmission, thereby ensuring reliable communication in the network.

Wang et al. [12] designed non-intersecting path algorithms from the perspective of multi-objective optimization. Firstly, three non-intersecting path construction algorithms were proposed based on the relative positions of any two different nodes in H. An algorithm for constructing non-intersecting paths between any two different nodes in H is provided. Then, the process of constructing non-intersecting paths in H using the non-intersecting path algorithm was simulated through experiments. In addition, simulation experiments have verified that the maximum length of the path obtained by the non-intersecting path construction algorithm proposed in this paper is only larger than the diameter of the same dimension. This indicates that in the worst-case scenario, the communication delay between any two nodes in H is relatively small. Wang et al. [13]

completed the research and implementation of the overall architecture of social network visualization analysis tools. A hierarchical architecture solution has been proposed. We have completed the component selection for visualized data presentation and selected a solution that is suitable for the actual situation of this project from multiple solutions through comparison. Based on this, the design and implementation of the visualization part of the prototype system were completed. It analyzed and studied the communication methods between the rich client and server, determined a reasonable data transmission and information exchange method, and ultimately implemented a communication mechanism. Analyzed and studied the key technical points in the project, and implemented data extraction algorithms and graphic data conversion algorithms. An analysis and research were conducted on the design of the interface, using human-computer interaction technology to improve the usability of the prototype system. A task-working mode was designed and implemented, greatly improving the usability of the system. By testing the prototype system implemented on existing systems, the effectiveness of the design and implementation was verified, and a large number of improvement suggestions were obtained through actual use by end-users, laying a good foundation for future work.

The study of disjoint paths in data centre networks is of great significance for their reliable communication performance. Non-intersecting paths can be used to maintain reliable communication between nodes in a network, mainly reflected in the following two aspects. If there are n non-intersecting paths between any two different nodes in a data centre network, then when conducting point-to-point communication in the network, the data packets to be transmitted are transmitted simultaneously along n non-intersecting paths from the starting node. This enables the terminal node to receive n copies of the same sent data packet (under normal circumstances). To reduce the packet loss rate during data transmission and improve the reliable communication performance between nodes in the network [14]. Xu [15] allocates the transmission power of the transmitter through signal power control, which is an effective way to reduce the interference generated by resource reuse fundamentally. However, from the above research work, it can be seen that factors such as diverse resource reuse modes, complex network scales, and inherent limitations of terminal devices must be considered comprehensively. The power control algorithms are established through mathematical programming to solve complex optimization problems. Then, methods such as Boman's theory and heuristic algorithms are used to solve the problem. This method requires a large amount of computing power and relatively high complexity. Similarly, current research has almost always focused on reducing interference between cellular users and visual users in multiplexing mode, with little attention paid to power control issues between visual pairs. The servers in the data centre network inevitably experience failures. Therefore, how to ensure reliable communication between servers in the data centre network has become an urgent problem to be solved. The communication reliability of data centre networks is a prerequisite and guarantee for reliable information transmission in a network. Since the proposal of the data centre network HSDC, research on this network is still in a relatively blank stage. As a highly scalable data centre network, studying the reliable communication performance of HSDC is of great significance. Therefore, Zhu et al. [16] will conduct research on the reliable communication performance of this network for the first time.

3 SOCIAL NETWORK ANALYSIS AND COMMUNICATION PATHS

3.1 Basic Theory and Method of Social Network Analysis

As the core of cloud computing, data centre networks transmit tens of thousands of information through them, ensuring the reliable communication performance of data centre networks is crucial. Data centre network visualization is a network that performs well in terms of incremental scalability. It is designed based on a hypercube network topology and retains many excellent characteristics of hypercube networks. This article obtains its logic diagram by making the switch transparent in communication visualization. Then, indicators such as connectivity, fault-tolerant unicast paths, disjoint paths, Hamiltonian properties, and fault-tolerant Hamiltonian properties were studied to measure the reliable communication performance of visual interaction. The methods of social network analysis mainly include network construction, network measurement and network model. Network construction is the first step of social network analysis, which involves how to extract the structure and relationship of social networks from actual social data. Common network construction methods include social network analysis based on questionnaire surveys and social network mining based on online social platforms. Network measurement is a key step in the quantitative analysis of social networks, which can help us to describe the topological characteristics of networks, the centrality of nodes and the cohesion of groups. The network model is an important tool to abstract and represent social networks, which can help us understand and predict the behavior and evolution of networks.

3.2 Algorithm and Model of Communication Paths

Communication Paths is based on social network analysis, and it reproduces and predicts the propagation process of information in the network through mathematical modelling and computer simulation technology. In information communication, it is very important to understand how information spreads in social networks. By training a naive Bayesian classifier, we can predict which category a given text instance is most likely to belong to, thus simulating the communication paths of information in social networks. In terms of communication paths data collection, the data collection process is shown in Figure 1.

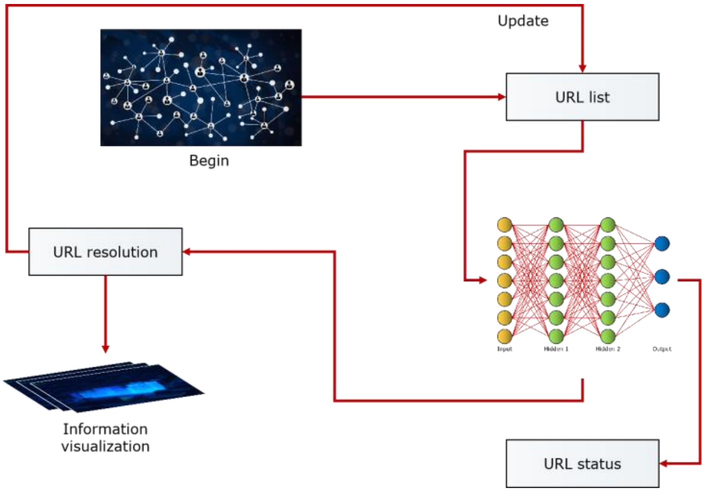

Figure 1: Data acquisition process.

The Naive Bayesian classification algorithm considers the words in a text as defining features for representing topics and news reports. The fundamental approach is to perceive the text as a compilation of unordered words. Initially, news reports in the training set undergo word segmentation, wherein $c_j \; 1<j<k$ signifies news topics, while $d = x_1, x_2, \cdots, x_i$ denoting news reports. Subsequently, the likelihood of a document d belonging to a category $c_j \in C \; 1<j<k$ is determined.

$$P \; c_j \middle| d \; = \frac{P \; c_j \; P \; d \middle| c_j}{P \; d} \tag{1}$$

$P\ c_j$ represents the prior probability, calculated as the proportion of documents in class c_j relative to the overall sample set. Meanwhile, $P\ d\big|c_j$ denotes the conditional probability of a document d occurring within class c_j.

In this study, the application of the N-Gram language model is employed for topic tracking. News d 's likelihood of belonging to each topic category, denoted as $P\ c_j\big|d$, is computed and assessed. Consequently, the news report d is assigned to the topic category c^* exhibiting the highest probability value:

$$c^* = \arg\max_{c_i \in C}\ P\ c_j\big|d \tag{2}$$

Since the denominator $P\ d$ remains consistent, determining the likelihood of news reports d belonging to various topic categories solely necessitates a comparison of the molecular value $P\ c_j\ P\ d\big|c_j$.

Measuring the similarity between users holds significant importance. Numerous methods exist to quantify user similarity, often expressed through distance metrics like the Euclidean distance. A smaller distance indicates a higher degree of similarity between two samples, while a larger distance signifies greater dissimilarity. Given two texts represented as a matrix D_i, D_j and $m \times n$, where each row of matrix m corresponds to a n-dimensional vector, the distance between these m vectors can be computed. Specifically, the Euclidean distance between two n-dimensional vectors $D_i = \ d_{i1},\cdots,d_{in}\ , D_j = \ d_{j1},\cdots,d_{jn}$ is determined using the following formula:

$$d\ i,j\ = \sqrt{\sum\nolimits_{k=1}^{m}\ d_{ik},d_{jk}\ ^{2}} \tag{3}$$

$$X = \ x_1, x_2, \cdots, x_{20} \tag{4}$$

In addition to supporting long-term task-based operations, the system also needs to support real-time manual association during design. This feature requires the system's client to be able to interact with the backend server dynamically. The client sends instructions back to the server, and the client needs to be able to dynamically accept the results returned from the server and display them on the interface. In this study, emotional analysis tools are used to score each piece of information. Then, these emotional scores are input into a naive Bayesian classifier as features to predict the communication paths of information in social networks. If a message is judged to have a positive emotional tendency, it can be assumed that its communication paths in social networks will be broader and deeper. On the other hand, if the information is judged to have a negative emotional tendency, its transmission path may be limited.

In social network analysis, a key challenge is to deal with the diversity and complexity of user-generated content. Especially on large social platforms, the information exchanged and published by users may involve a wide range of topics, and the direct analysis of this information may encounter problems such as dimension disaster, data sparsity and inaccurate measurement. In order to solve these problems, the Latent Dirichlet Allocation(LDA) topic model can be introduced, which can transform the high-dimensional relationship between users and vocabulary into the low-dimensional relationship between users and topics, as well as topics and vocabulary. When a netizen disseminates information, they have an opportunity to express and release their emotional viewpoints, resulting in a constant benefit value of 1. Conversely, if they refrain from expressing their emotions, the benefit is set to 0. The overall expected utility U is derived by considering the relative significance of emotional expression utility and communication income utility, represented by the weight ω:

$$E\left(U\right)=\frac{E\left(U_E\right)+\omega * E\left(U_p\right)}{1+\omega} \tag{5}$$

The Latent Dirichlet Allocation (LDA) theme model effectively reduces the dimensionality between users and vocabulary by mapping them onto two distinct dimensions: users and topics, as well as topics and vocabulary. This approach addresses issues related to sparsity and measurement inaccuracy. Furthermore, the KL divergence (also known as relative entropy) can be employed to quantify the relationship between two probability distributions:

$$KL\left(p_i \| p_j\right)=\sum p_i\left(x\right)\log\frac{p_i\left(x\right)}{p_j\left(x\right)} \tag{6}$$

In this context, p_i and p_j denote the theme vectors for users i and j, respectively. The higher the KL divergence, the stronger the correlation between these two users.

When information is disseminated, the benefit value of the information is updated according to the benefit of the communicator. For example, if the communicator gets positive feedback or recognition from communication paths, then the benefit value of the information can be increased. On the other hand, if the communicator does not get any benefit or receives negative feedback, then the benefit value of the information can be reduced. In the simulation process, a naive Bayesian classification algorithm is used to predict the communication paths of the given information, and the prediction results are adjusted according to the benefit value.

3.3 Combined Application of Social Network Analysis and Communication Paths

The combined application of social network analysis and communication paths is mainly reflected in two aspects: one is to use the results of social network analysis to guide the process of communication paths; The second is to feed back the results of communication paths to social network analysis to verify and improve the analysis results. In the aspect of using social network analysis to guide communication paths, the key nodes and group structures in the network are identified by analyzing the topological structure, node attributes, and edge weights of social networks. Then, in the simulation process, these key nodes and group structures are focused on and analyzed to reveal their functions and influences in the process of communication paths. In marketing, opinion leaders and potential consumers are identified by analyzing consumers' social networks, and then their purchasing decisions and behaviours are influenced by targeted marketing strategies.

Through the theme modeling of user-generated content, we can identify the main topics and hidden theme structures that users care about, which is of great significance for understanding the dynamics of social networks, predicting the trend of communication paths, and revealing users' interests and behavior patterns. Combined with the output of the LDA model, the accuracy and effectiveness of communication paths can be improved. To accurately categorize users based on their interests and knowledge backgrounds, primary consideration is given to user authentication information. Using this information, users can be placed into suitable categories provided by websites. For regular users, their respective categories are approximated using their forwarding data:

$$d=\sqrt{\sum_{n=1}^{k}\left(r_n-c_n^i\right)^2} \tag{7}$$

Here, m signifies the component within the one-dimensional vector r, representing the types of users forwarded. c_n^i corresponds to the specific user type vector component linked to distinct attribute characteristics i, serving as user categories. d denotes the degree of similarity between user traits and their respective user categories. Using these calculations, regular users can be effectively categorized.

The interest-driven model posits $t=0,1,\cdots,n$, that events $i, i=1,2,\cdots,n$ occur discretely at each time step. The likelihood of activity at t the moment stands at $\gamma(t)$, while τ_i represents the duration between successive events. Assuming T_1, T_2 as two thresholds and $T_1 < T_2$, the $i+1$ event transpires at t.

$$\gamma(t+1)=\alpha(t)\gamma(t) \tag{8}$$

$$\alpha(t)=\begin{cases}\alpha_0, & \tau_i \le T_1 \\ \alpha(t-1), & T_1 < \tau_i < T_2 \\ \alpha_0^{-1}, & \tau_i \ge T_2\end{cases} \tag{9}$$

In this context, $\alpha_0 \in (0,1)$ signifies the rate of alteration and the likelihood of activity occurrence. When $T_1 \le T_2$ it becomes evident that the model's distribution approximates the curtain law function.

In the aspect of feeding back the results of the communication paths to social network analysis, the results of social network analysis are verified and improved by comparing the simulation results with the actual observation data. The topic model yields the distribution matrix of words about each topic, denoted as a parameter ϕ. Keyword i can be represented as a theme vector ϕ_x. Cosine similarity is employed to determine the similarity between keywords.

$$Sim\_s(x,y)=sim\_\cos(\phi_x,\phi_y) \tag{10}$$

Supposing social media data spans over T days, with each day designated as a time node, the signal about the word w can be enumerated as a sequence of length T, as outlined below:

$$S_w=\left[s_w(1), s_w(2), \cdots, s_w(T)\right] \tag{11}$$

$s_w(t)$ represents the frequency with which keywords appear within the designated time frame t. To enhance convenience, this study converts the distance formula of samples into a similarity formula. Consequently, the time series similarity of keywords w_i, w_j is formulated as follows:

$$Sim\_t(i,j)=\frac{1}{1+DTW(S_i,S_j)} \tag{12}$$

Analogous to the approach used for constructing the semantic similarity matrix, a time-series similarity matrix T for keywords is also established. Likewise, the element $T_{i,j} \ge 0$ within this matrix signifies the temporal sequence similarity of the keyword w_i, w_j.

By using advanced social network analysis methods and communication paths technology, we can better understand the structure and behaviour characteristics of social networks and predict and deal with various problems in the process of communication paths. This method of social network analysis and communication paths integrated with the LDA theme model can not only effectively reduce the dimension and complexity of data but also improve our ability to understand the process of social network communication paths by transforming the high-dimensional relationship between users and vocabulary into two more compact and easy-to-explain dimensions, social network data can be analyzed more efficiently. Hidden structures and useful information can be mined.

4 CAD SYSTEM AND COLLABORATIVE VISUALIZATION

With the rapid development of information technology, CAD systems have expanded from the traditional engineering design field to many disciplines and industries. Especially in dealing with complex data and realizing advanced visualization, CAD system shows their unique advantages. In social network analysis and communication path simulation, collaborative visualization by using a CAD system can greatly enhance the intuition of analysis and help researchers and decision-makers better cope with the challenges in the process of communication paths.

The powerful 3D modelling and data processing capabilities of CAD systems enable them to display complex social network data in an intuitive and easy-to-understand way.

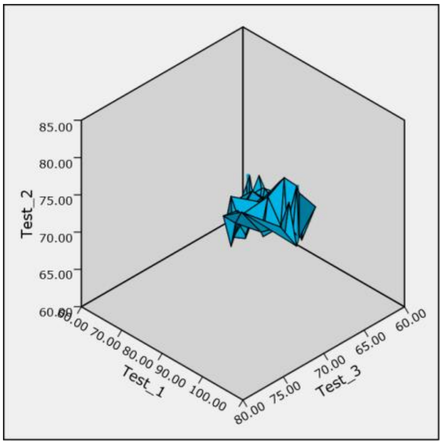

Figure 2: Social network propagation prediction.

Figure 2 shows the prediction of social network propagation. Connectivity is an important indicator for measuring the reliable communication performance of a network. The greater the connectivity of a network, the stronger its fault tolerance and reliable communication capabilities. When the number of faulty nodes in the network is less than its connectivity, there is at least one fault-tolerant unicast path between any two different faultless nodes in the network to ensure reliable data transmission between the node pairs. We can integrate the communication paths algorithm with the CAD system to realize real-time visualization and interaction of simulation results. In this way, the communication paths of information, the state changes of nodes and the overall dynamics of the network can be observed in real-time during the simulation process. This is of great significance for understanding the communication paths mechanism, identifying key communication nodes and evaluating the effects of different communication strategies. Figure 3 shows the simulation results of social network visualization data.

Collaborative visualization can also support multi-user collaboration and sharing. Through the network connection, multiple users can access and operate the same visual scene at the same time, and make analyses and decisions together. This is of great significance for teamwork and remote collaboration, which can greatly improve work efficiency and accuracy.

5 CASE ANALYSIS AND EXPERIMENTAL VERIFICATION

As important content related to public life, the communication paths and effect of health information in social networks are the key factors in studying the spread and influence of information. In a relatively stable and closed social network environment, health information can be effectively disseminated and covered. However, the dynamic changes in the network environment will have an uncertain impact on the dissemination of health information. Therefore, we use the social network analysis method and CAD collaborative visualization technology to simulate the transmission path of health information. First, the hot topic discovery method is used to identify health-related topics in social networks (as shown in Figure 4). These data not only reflect the user's interest in health information and the hot discussion but also provide a basis for the subsequent communication paths.

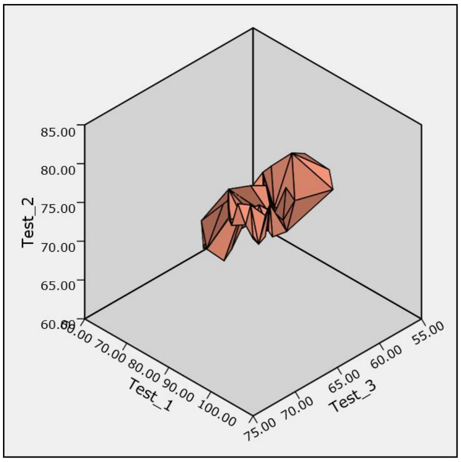

Figure 3: Visual data simulation of social network.

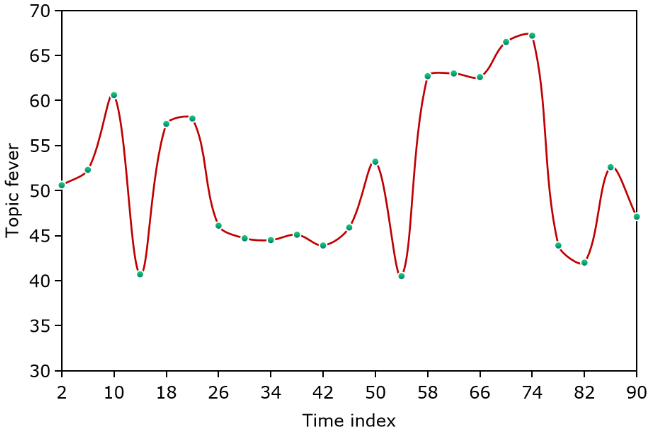

Figure 4: Time series diagram of health information topics.

In order to support the effective dissemination of health information, we built a health communication paths database to meet the needs of users for health information resources. Various health information contents are gathered in the database, allowing users to query, share and contribute knowledge.

In order to simulate the transmission path of health information more accurately, the traditional information transmission model was optimized in this study, and experiments verified the optimized model. The test results show that the proposed model can converge quickly in the training process and show good performance (as shown in Figure 5).

In addition, the relationship between the heat of information discussion and the scope of communication is also discussed (as shown in Figure 6). The results show that health information with high discussion has a wider spread in social networks. This discovery provides a useful reference for formulating targeted health communication path strategies.

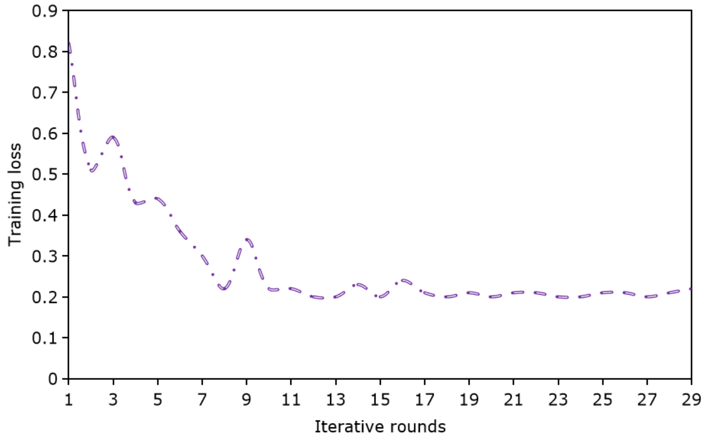

Figure 5: Training loss curve.

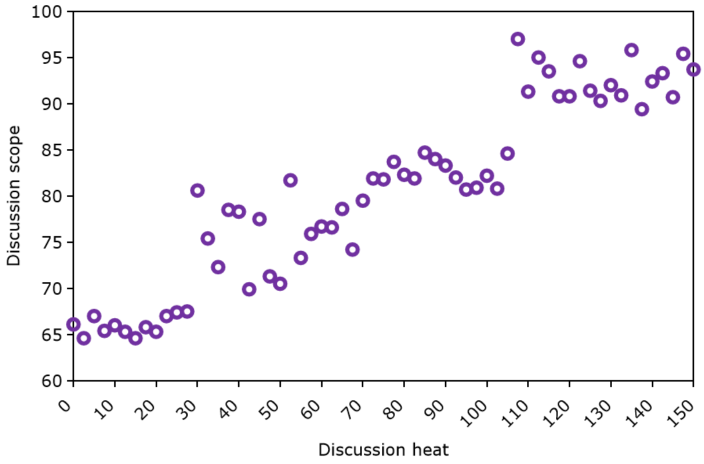

Figure 6: Curve of health communication paths range changing with discussion heat.

Finally, the performance of the proposed method is comprehensively assessed (as shown in Figure 7). Compared with other methods, the method proposed in this article shows higher efficiency and accuracy when dealing with a large number of data. This further verifies the practicability of the proposed method in the simulation of the health information transmission path.

Through the research and analysis of the experimental part, we verify the effectiveness of social network analysis in the simulation of health information transmission path and the important role of CAD collaborative visualization in the analysis process. These achievements have important practical significance for improving the effect of health communication paths and optimizing communication paths strategies.

6 CONCLUSIONS

This article discusses the importance of social network analysis in revealing the communication paths mechanism and emphasizes the value of communication path simulation and CAD collaborative visualization in enhancing our cognition of complex social networks. By integrating these advanced technologies and methods, we can more accurately predict the diffusion speed, scope and influence of information in social networks, and provide scientific decision support for marketing, public communication paths and crisis management.

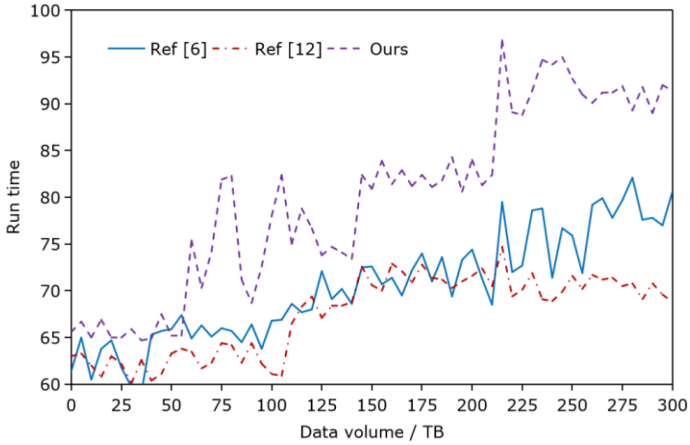

Figure 7: Performance comparison of different methods for processing health communication paths data.

Social network analysis can not only gain insight into the dynamics of key nodes and groups in the network but also reveal the patterns and influencing factors of information flow. On this basis, the communication paths further predict the propagation process of information in different network environments, which is helpful for us to formulate more effective communication paths strategies. At the same time, the application of CAD technology enables social network data and simulation results to be presented more intuitively and understandably, which greatly enhances the understanding of network structure.

By integrating the technologies and methods of social network analysis, communication paths, and CAD collaborative visualization, we can manage the information resources in social networks more effectively and promote the development of information communication science. Future research can further explore the integration of these technologies and methods to exert their potential in more fields.

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