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Research Article

Relational Graph Construction Method and Information Management System Based on the Relational Graph Convolutional Network

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The Internet is like a huge neural network that is thought to be built, linking all the information in the human brain, and the communication between people is a part of the communication in the whole society. Social products are the medium of communication between people, so the efficiency of social products directly affects the efficiency of people and even the whole society. This paper mainly focuses on social applications as the object to carry out research. This paper is dedicated to optimizing the user experience and social experience of mobile social products, optimizing the design strategies of each process of social products, and exploring the possibility and development direction of social products in the future. Firstly, it conducts in-depth research on the related theories of human social behavior based on the social relationship graph and summarizes the factors that affect the intimacy between nodes in the social relationship graph. Then, it discusses the role of these factors in designing social products and studies how to apply these factors to all aspects of product development. Then, this design method using intimacy factor is abstracted and summarized into a design model, which is convenient for product developers to understand and use. Finally, the practice shows that the mobile social design method based on the social relationship graph can effectively guide the design of mobile social products and provide users with an intimate and efficient social experience that can meet the social needs of users. The accuracy rate is effectively improved by 21%, which proves the value and prospect of the research, design, and development of this topic in the field of mobile social products.

1. Introduction

People's basic life is inseparable from social interaction. People are social animals, and social needs are as indispensable as basic physiological needs. Socialization is the basic condition for human beings, and people without socialization are just like animals, because the society is the environment that shapes personality. The birth of the Internet is called the information revolution, because its development and popularity exceeded people's expectations. The biggest difference between the Internet and the traditional telecommunication network is the structure. The telecommunication network is the structure from the backbone to the branch. Just like the blood vessel network of the human body, if any node has a problem, it will definitely affect the function of its lower nodes. The structure of the Internet is a net-like structure, just like a fishing net. Problems in the nodes do not affect the overall operation, which is similar to the neural structure in the human brain. Nerve users disseminate electrical information, while blood vessels are used to conduct fluids, so the topology of the Internet is naturally more suitable for information dissemination. The Internet is like a huge neural network that is thought to be built, linking all the information in the human brain, and the communication between people is a part of the communication in the whole society. Today, with the popularity of social networks, various Internet service companies are gradually realizing the importance of social networking. They have created various social products or are eager to socialize their products. Social products are the medium of communication between people, so the efficiency of social products directly affects the efficiency of people and even the whole society.

A relational graph is a graph-based data structure. Graphs are often used to represent user interactions, but some algorithms are no longer practical for analyzing large graphs. Bartal and Ravid introduced a new algorithm that does not exist yet to represent large user interaction graphs, and their proposed algorithm was applied in different ways to two large datasets [1]. Inferring social relationships from user location data is becoming increasingly important in real-world applications. The observed encounters between two users may be rare due to limitations and biases in real-world data collection. Yu et al. proposed to build a user graph based on spatiotemporal interactions and use graph embedding techniques to learn user representations from the graph [2]. This review by Al-Jawadi and Al-Shumam was based on an understanding of the key concepts between computer engineering and mathematics, and they also believe that most students face the same problem, because they lacked foresight on the link between specialized learning materials and general materials [3]. Volumetric pulse wave densitometer (PPG) sensors are suitable for portable devices and can provide a wide range of information. Of particular importance, the reflective PPG sensor can be easily placed anywhere on the body with minimal constraints on the user. Therefore, Nogami et al. believed that it is important to reduce the DC signal and improve the AC-DC ratio [4]. The above scholars have done specific research on the relationship graph, but they have not explained the research methods in detail, and they can be supplemented in the future.

Graph convolutional networks are a method of deep learning. Maser MR has developed machine learning classification models to predict crosslinking reaction conditions for specific substrates. For each dataset, experts compiled a unique vocabulary of reactants to classify response coefficients and make situation-specific predictions [5]. Ohtomo et al. proposed a method to provide personalized recommendations for each user based on a large number of publications. By applying a convolutional graph network (CGN) to each target user, it is possible to match precise recommendations to each user's preferred posts [6]. Paraschiv et al. focused on certain unfounded conspiracy theories between 5G networks and the spread of COVID-19. They showed that tweets supporting these theories can be detected by state-of-the-art deep learning models. It is also possible to transfer learning objectives from tasks related to fake news and propaganda, improving the performance of our model [7]. Pu et al. believed that the porous structure can not only prevent aggregation but also allow more GCN to be exposed at the active site [8]. Although these scholars have done a complete study of the graph convolutional network, they have not explained it based on the relational network and lack some pertinence.

The novelty of this paper is as follows: the design of mobile social products for real social networking on the market is very simple. This paper attempts to start from the research of the social relationship graph to explore the differences of people's social interaction at different relationship strengths and the factors that affect the strength of social relationships, which in turn guide the design of social products. It gives social product developers a new perspective on social products and then creates more innovative social products to serve the majority of users.

2. Graph Convolutional Network Algorithm

2.1. Graph Theory and Graph Learning. Generally speaking, graphs in graph theory are often used to describe a certain relationship between different objects. Points are used to represent different objects, and edges between two points are used to represent the relationship between the corresponding two objects [9].

2.1.1. Diagram Structure. Graphs are an important part of combinatorics and discrete mathematics. It is a mathematical structure used to model data relationships. A graph is fully connected if all nodes in a graph have $m-1$ adjacent nodes. The adjacency matrix B represents the connection relationship of the edges between nodes, which is expressed as follows:

$$b_{rt} = \begin{cases} 1, & (n_r, n_t) \in G, \\ 0, & \textit{otherwise}. \end{cases} \tag{1}$$

In general, graphs may be directed or undirected. If the edges of the graph are ordered, it is called a directed graph; otherwise, it is called an undirected graph. If it is a directed graph, the value of the adjacency matrix is the weight of the edge. Figure 1 is the basic geometric interpretation of the graph.

2.1.2. Laplacian Matrix of the Graph. The Laplacian matrix of a graph has a lot to do with the adjacency matrix, $h_{r,r} = \sum_{t=1}^{M} b_{r,t}$. In the deep neural network model, the symmetric normalized Laplacian matrix is defined as follows:

$$F^{s\times n} = H^{-(1/2)} F H^{-(1/2)} = U - H^{-(1/2)} B H^{-(1/2)}, \tag{2}$$

L is the identity matrix.

2.1.3. Hypergraph Learning. The traditional point-to-point graph cannot effectively describe the complex relationship between data, which affects the quality of the graph [10]. So, the correlation moment F is defined as follows:

$$f(n, g) = \begin{cases} 1, & \text{if } n \in g, \\ 0, & \textit{otherwise}. \end{cases} \tag{3}$$

According to the association matrix F, the degree of each vertex is expressed as follows:

$$h(n) = \sum_{g \in G} p(g) f(n, g). \tag{4}$$

The degree of each hyperedge $g \in G$ is expressed as

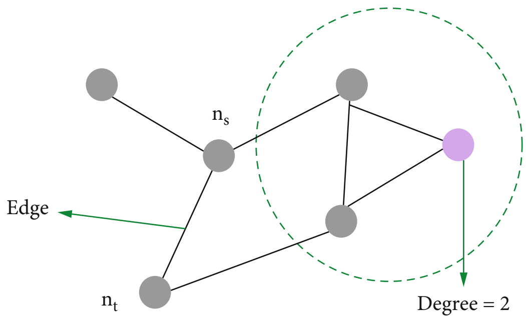


Figure 1: Schematic diagram of nodes and edges.

follows:

$$\varphi(g) = \sum_{n \in N} f(n, g). \tag{5}$$

Define a standard hypergraph as follows:

$$B = \mathrm{GWG}^R - S_N. \tag{6}$$

The normalized hypergraph Laplacian is expressed as follows:

$$F_M = U_M - H_n^{-(1/2)} GWH_s^{-1} G^R H_n^{-(1/2)}. \tag{7}$$

U_M is an identity matrix. In a simple graph, the edge matrix H_s is equal to 2 U_M. Figure 2 is a geometric interpretation of a hypergraph.

2.2. Graph-Based Semisupervised Learning. Unsupervised learning is mainly used when the sample set is not labeled and the cost of manual labeling is too high or the structural characteristics of the sample obviously do not require labeling information. The prediction accuracy of supervised learning is better than that of unsupervised learning algorithms, because there is a lot of reliable labeled data in supervised learning, but it requires a lot of manual labeling information, which greatly reduces the efficiency of model learning. However, there is no reliable labeled data in unsupervised learning, which will lead to lower prediction accuracy [11]. Figure 3 shows semisupervised learning by introducing unlabeled samples in model training when the number of labeled samples is small.

2.2.1. Euclidean Distance. Euclidean distance refers to the distance between two points in space, namely,

$$f_{ab} = \sqrt{(y_a - y_b)^2}. \tag{8}$$

2.2.2. Representation of Manhattan Distance.

$$f_1 = |y_a - y_b|. \tag{9}$$

2.2.3. Representation of Chebyshev Distance.

$$f_{\infty} = \sqrt[\infty]{(y_a - y_b)^2}. \tag{10}$$

2.2.4. Mahalanobis Distance. The Mahalanobis distance is defined as follows:

$$F = \sqrt{(y_a - y_b)^T D^{-1} (y_a - y_b)}, \tag{11}$$

where D is the covariance matrix.

Another important aspect of graph-based semisupervised learning is label propagation. To propagate class labels through edges, define the probability transition matrix as follows:

$$Q_{ab} = Q(a \longrightarrow b) = \frac{\alpha_{ab}}{\sum_{j=1}^{u} \alpha_{aj}}. \tag{12}$$

2.3. Graph Convolutional Neural Networks. Figure 4 is the overall framework of the convolutional neural network, and therefore, the graph convolutional neural network is proposed.

2.3.1. Graph Convolutional Network Based on the Spectral Method. The spectral method takes the node attribute as the signal in the graph and directly performs the convolution operation on the spectrum of the graph (i.e., the singular value of the graph Laplacian).

The spectral convolution of filter $f^{\beta} = diaf(\beta)$ in the Fourier domain is as follows:

$$f^{\beta * y} = N f^{\beta}(\Lambda) N^R y. \tag{13}$$

However, the computational complexity of singular value decomposition is too high. In order to overcome this difficulty, the spectral filter is approximated by the q^{th} -order Chebyshev polynomial as follows:

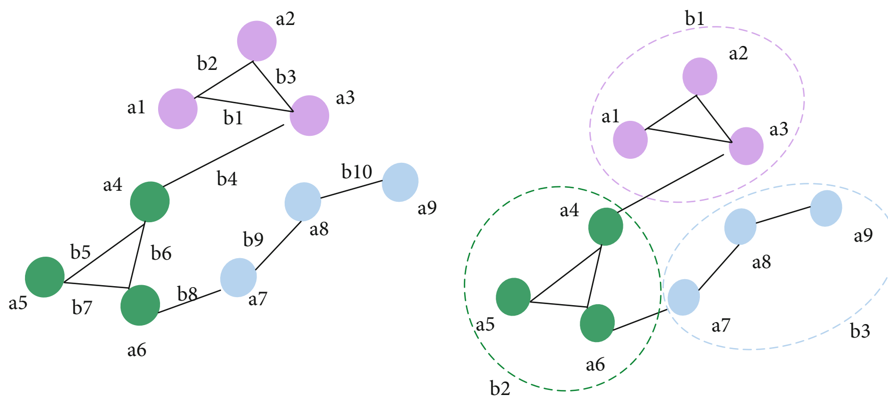
$$f^{\beta * y} = \sum_{q=0}^{q} \beta_q R_q(K) y. \tag{14}$$

R_q and β_q are the Chebyshev polynomials and coefficients, respectively, and the Chebyshev graph convolution is further simplified as follows:

$$f^{\beta * y} = \beta\left(U + F^{-(1/2)} B F^{-(1/2)}\right) y. \tag{15}$$

If the signal y has x input channels and d spectral filters, the convolution formula is expressed as follows:

$$G^{(u+1)} = \operatorname{Re} KN\left(\tilde{F}^{-(1/2)} \tilde{B} \tilde{F}^{-(1/2)} G^{(u)} \Theta\right). \tag{16}$$



(a) Simple graph (b) Hypergraph

Figure 2: The difference between a simple graph and a hypergraph.

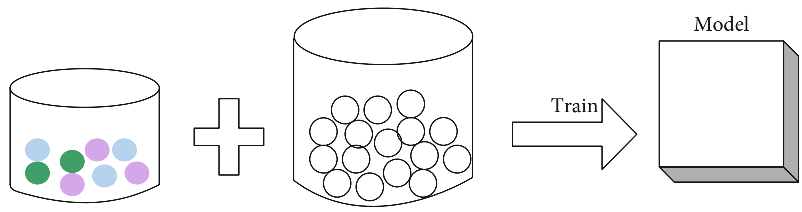


Figure 3: Semisupervised learning example.

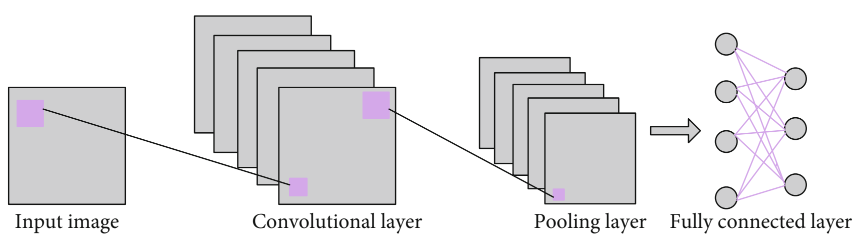


Figure 4: Flowchart of the convolutional neural network.

The final output layer S is defined as follows:

$$S = soft\max\left(\widehat{B}\,\mathrm{Re}\,KN\left(\widehat{B}Y\Theta^{(0)}\right)\Theta^{(1)}\right). \tag{17}$$

Among them, $\widehat{B} = \tilde{F}^{-(1/2)}\tilde{B}\tilde{F}^{-(1/2)}$, $soft\max(\cdot)$ are nonlinear activation functions.

2.3.2. Graph Convolutional Networks Based on Spatial Methods. Spatial methods use the idea of information aggregation of adjacent nodes to define convolution operations directly in the spatial domain. Then, the convolution operation of each layer can be expressed as follows:

$$G = d\left(M^{x} \otimes Q * Y\right). \tag{18}$$

V is the number of nodes and D is the number of features.

Rebuild the existing model and define it as follows:

$$g_n^r = N\left(g_n^{r-1}, \sum_{m\in U(n)} W_r\left(g_n^{r-1}, g_m^{r-1}, e_{nm}\right)\right). \tag{19}$$

3. Mobile Information Management Design Based on the Social Relationship Graph

3.1. Development Trend of Social Networks. With the rapid development of information technology, the development of social networks presents the trend of "mobilization" and "instant communication." Figure 5 shows some of the most highly valued startups worldwide.

The "mobile" trend refers to the transfer of Internet products from computers to mobile terminals such as mobile phones. The main function of the computer is to "work," and the user must sit in a fixed position in a relatively upright sitting position in order to use the social network on the computer. Even a laptop computer increases mobility, but it is nowhere near as good as a mobile phone

Figure 5: Some of the world's most valuable startups.

that can be pulled out of pocket to check social networks anytime, anywhere [12]. The evolution of devices has forced the form of social networks to follow this change and become more mobile friendly. For example, QQ was born in computer social products, while WeChat was born in mobile terminal. Therefore, QQ's input is more accommodating to computer keyboard input and mouse input, while WeChat emphasizes voice input, avoiding the dilemma of mobile phone keyboard input. Since the ease of accessing the Internet on the mobile terminal is much higher than that on the computer terminal, the activity and stickiness of the social network on the mobile terminal are naturally much higher than that on the computer terminal, just like WeChat has a great momentum to replace QQ.

The trend of "instant messaging" refers to the rapid development of instant messaging products. Instant messaging refers to products like QQ. The main product function is point-to-point dialogue. Compared with Facebook's emphasis on personal page display and dynamic attention, instant messaging products are more suitable for the needs of mobile terminals. The main reason is that the initial function of the "mobile phone" is a point-to-point instant communication—"calling." Mobile phones are designed for calls at the beginning, and even if various other functions are derived later, point-to-point calls are always the most suitable for mobile phones. The screen size of mobile phones is not as large as that of computers, so it cannot display personal homepages and dynamic information as well as Facebook. When people use mobile phones, they do not have the same stable table, quiet environment, and calm mood as when using computers, so the reading experience of mobile phones is far lower than that of computers, and the advantages of mobile phones are instant and voice input.

3.2. Influence of the Social Relationship Graph on the Mobile Social Product Design

3.2.1. The Development History of the Social Relationship Graph in Social Products. At the beginning of the development of social products, users did not successfully transfer the real-world social relationship graph online, so the design of early social products did not consider the user's social relationship graph. The birth of Facebook has brought social products into a new era. Facebook has successfully reproduced the user's social relationship graph online. Early social networks were mostly based on the theory of six degrees of separation, and people could use social networks to get to know people outside the real social world. People mainly socialize with strangers. In order to protect their privacy, people usually choose to use a virtual identity, that is, use anonymous communication. Anonymity is the biggest difference between virtual social and real social. Under the protection of anonymity, a person's self-disclosure can reach the maximum value and an individual can reveal all his privacy to the other party, because this behavior will not bring losses and influences to him in real life [13]. Complete self-disclosure does not mean the strongest bonds and intimacy between individuals. When people are completely free from social norm constraints and social responsibility constraints, the cost of dishonest behavior is reduced to zero, reciprocal behavior between individuals is difficult to produce, and social utility is impossible to talk about. It is difficult to generate trust among individuals, and it is also difficult to generate cooperation. Therefore, people cannot have strong connections with each other based on this virtual social interaction, as shown in Figure 6.

With the improvement of the interactivity and efficiency of Internet social products, people gradually realize that

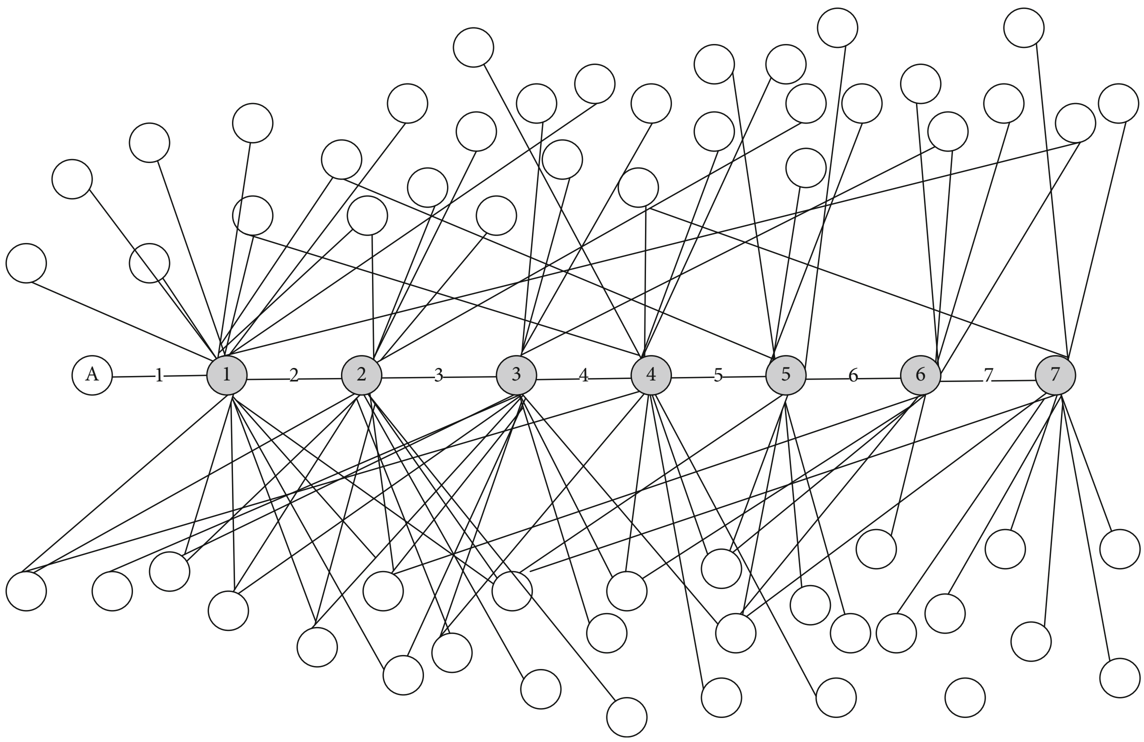


Figure 6: Schematic diagram of the six-dimensional space theory.

social products in the virtual world can provide convenience for real social interaction. Therefore, in the process of using the product, gradually establish a mapping of their own social reality in the virtual world.

3.2.2. Form Classification of Social Products Based on the Social Relationship Graph. Different social products have different product forms, and the product form is the overall form presented after the integration of all aspects of the product's strategy, function, architecture, and design. The shape of each product is unique, but it can be classified using certain dimensions. The following is to classify the forms of existing social products based on the social relationship graph. The purpose is to clarify the positioning of the product in the market. It found market opportunities and analyzed the pros and cons of various products, as shown in Figure 7.

(1) Strong Contact Product. Now, the strong connection products on the market are instant messaging products. Instant messaging products belong to point-to-point communication. This product form has the highest efficiency, the highest cost, and the highest privacy. It does not mean that instant messaging is the only product form suitable for strong social contact.

(2) Contact the Product in. The product form of China Contact includes more multipoint social functions such as groups and dynamics. The reason is that the number of contacts at the contact level is large and the cost of using the point-to-point form is too high [14]. There is no product specially designed for medium contact, and users now use some functions in strong contact products to socialize in medium contact. For example, group chats in WeChat and Moments are suitable for social networking, while private chats are suitable for strong social networking.

(3) Weak Contact Products. The number of weakly linked products is large and the product forms are diverse. Representative Twitter and Weibo are two products that give full play to the advantages of information dissemination in weak-contact social networking, and the product form is designed as an information flow, which is beneficial for users to receive the latest information. Google+ gives users the power to control the scope of information dissemination, while Momo pays more attention to getting to know more strangers. No matter how diverse their forms, the common denominator is low social cost and low privacy.

(4) Temporary Contact Product (No Contact). Temporary contact products are divided into two categories, the first category of products is only used for temporary lightweight social networking when using certain nonsocial products. This kind of product is not a social product, but only the social function part of the product. The central purpose of social is to acquire content, not to build lasting connections. Therefore, the temporary contact product only needs some lightweight social functions with extremely low cost to meet the needs of users. Dianping, next kitchen, etc. belong to this category. The second category belongs to the category of social products. The function of the product is to help users get to know strangers, such as Momo and invite to dinner.

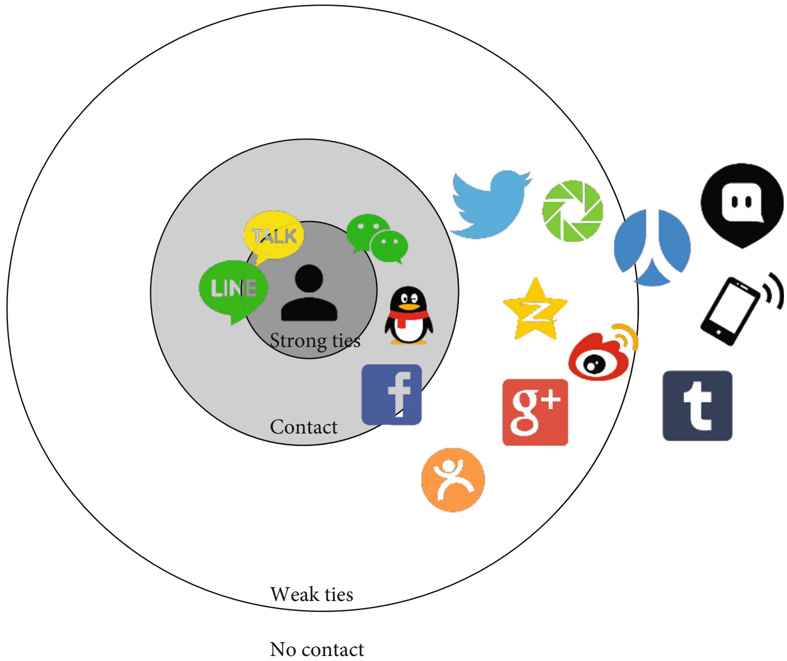


Figure 7: Social products at different social intensities.

To sum up, different products cover different scopes of social relationship graphs and the scope of product selection is based on the strategic positioning of products. Taking WeChat as an example, WeChat was initially positioned in peer-to-peer social networking and focused on strong-connected social networking. When WeChat itself develops to a certain scale, it gradually adds internal functions to cover more social relationship graphs. WeChat group chat, Moments, and Shake functions are all designed for different social scopes. Different social relationship graph ranges represent the social behavior of individuals when they contact people with different relationship strengths. When designing social products, it is necessary to identify the differences in social behavior of different relationship strength levels, so that the products can fully meet the social needs of users [15]. There are not many products based on strong ties, and none of them are products with high popularity. Existing strong-connection products, such as WeChat, do not optimize the user experience of strong-connection social networking well. Therefore, through the research of this paper and this project, we try to create a product form that is more suitable for strong social connection.

3.3. Design and Implementation of the Social Relationship Personal System. The role of the personal analysis application system is to display the effects of the various analysis algorithms mentioned above. This system is part of the whole microblog analysis system. Its main task is to analyze and visualize the characters in Weibo. The system is a direct application of the research in this paper, and it is a concentrated embodiment of user relationship analysis and content analysis. This section will introduce the design idea and function embodiment of the system in detail.

The system mainly conducts relevant data analysis around individuals in Sina Weibo. The system first needs a source of data, that is, the microblogging crawler. It is used to crawl all information related to an individual (personal social circle, all microblogs posted by an individual, all microblogs received by an individual, and behavioral information of an individual). Then, these information are used to calculate with the character relationship analysis algorithm, topic identification algorithm, and recommendation algorithm given above. The main analysis includes the following: relationship closeness calculation, community discovery, topic identification, and character recommendation.

The source, overall framework, functions, and visual display of the personal analysis application system for Weibo are introduced in detail as follows.

3.3.1. System Source. The microblog analysis system actually includes three aspects: individual analysis, group analysis, and event dissemination analysis. Personal analysis corresponds to the analysis of a single person in the system, and group analysis corresponds to the analysis of a field group, such as the field of information retrieval and machine learning. Time propagation analysis mainly analyzes a single microblog published by a character [16]. Personal analysis is an indispensable part of the whole system, which is particularly important. Figure 8 presents the research framework of the entire microblog analysis system and clearly marks the location of the personal analysis.

3.3.2. The Overall Framework of the Personal Analysis System. The overall framework of the personal analysis system based on Weibo is divided into five parts, crawler, character analysis, information recommendation, character recommendation, and visualization.

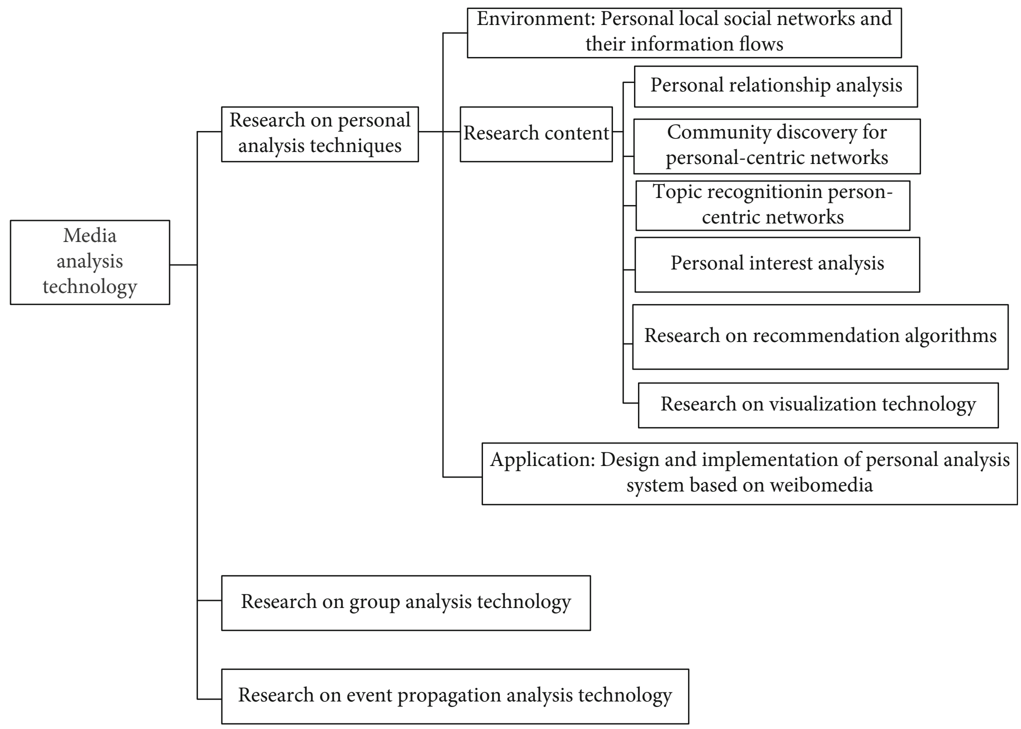


Figure 8: Research framework of the overall system.

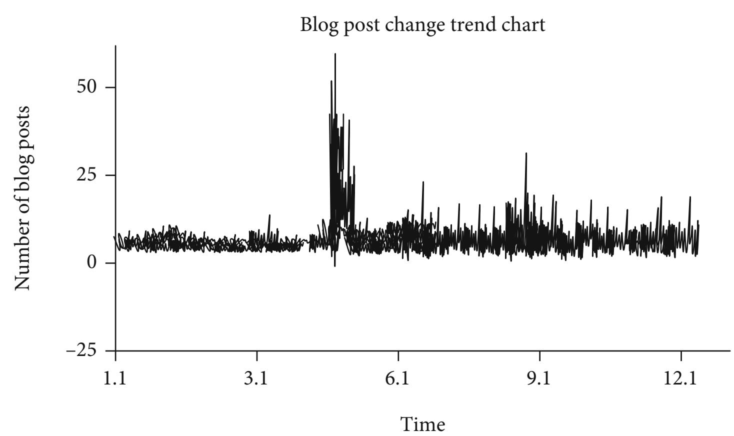


Figure 9: Trend graph of blog posts.

The overall framework description is as follows: first of all, the data source of the system is Sina Weibo and Sina Weibo is selected because it is actually the largest social media with the most active users in China. After the data source of the system is determined, the crawler is designed to crawl the data and the data is stored in two parts. One part is the user relationship and attribute data, and the other part is the content and behavior data. After data crawling, the data is cleaned, and finally, three types of information can be obtained: basic information of characters, relationship information, and Weibo information. Feature extraction is performed on the above information to extract useful features for subsequent analysis. The analysis is carried out from three aspects, community discovery, relationship analysis, and topic analysis, and finally, the results of the analysis are visualized [17]. Below the whole framework are two parts: information recommendation and character recommendation. Information recommendation calculates the correlation between character characteristics and information. At the same time, the ranking of the recommendation results is carried out with reference to the value of the information itself and the explanation of the recommendation is given at the same time and finally displayed through visualization. The difference between person recommendation and information recommendation is that person recommendation calculates the correlation between characters. The system uses a combination of the person recommendation method based on the relationship graph and the person

Table 1: Popularity recommendation accuracy and recall.

N	Recall	Accuracy
5	0.051	0.29
10	0.072	0.25
15	0.113	0.23
20	0.135	0.22
25	0.166	0.21
30	0.188	0.19

Table 2: Common character recommendation accuracy and recall.

N	Recall	Accuracy
5	0.010	0.53
10	0.021	0.49
15	0.032	0.46
20	0.043	0.42
25	0.045	0.40
30	0.049	0.39

Table 3: Accuracy and recall of all characters recommended.

N	Recall	Accuracy
5	0.008	0.47
10	0.016	0.44
15	0.023	0.41
20	0.029	0.39
25	0.035	0.38
30	0.042	0.36

recommendation method based on content matching to rank the recommendation. At the same time, the recommended explanation is given as well as the final visual output results.

The whole system is developed with B/S architecture, which can support crossplatform access. The system uses HBase as the storage engine, which can withstand the test of big data. In order to better show the effect of analysis, the display part of the system adopts a lot of Html visualization technology. At the same time, in order to increase the speed of system access, the system adds a memcached module on the server side, which can improve the access speed of users.

3.3.3. System Function. The whole system uses a variety of visualization techniques to visualize the results of the analysis, and the part of people's interest is displayed in the form of keyword cloud. The relationship strength part is displayed in the form of a relationship diagram, and the topic analysis is displayed in the form of a pure web page. At the same time, the relationship network of characters is displayed in the way of the relationship graph.

The character analysis system is a part of the whole microblog analysis system, and its entrance mainly includes the search part, the group analysis part, and the dissemination analysis part. For example, if the searched user does not exist in the database, the user will be added to the list of crawling characters. The background program will automatically crawl, as will the group analysis part and the propagation analysis part.

(1) Content Visualization.

(i) List of Blog Posts

Weibo media is a platform that allows users to freely publish and forward information. Therefore, after the accumulation of time, each user will have his own microblog list and the system will display the user's blog post list to the user in the form of a table. Different from the microblog list function provided by Sina Weibo, the system provides the function of searching and sorting by time, number of retweets, and number of comments, so that users can better query the microblogs that they need.

(ii) Analysis of Changes in Blog Posts

If a person's Weibo is counted by time, it can show a certain trend and can be used to measure the user's activity on Weibo [18]. This system counts all microblogs published by a person by time, counts the number of blog posts published every day, and then draws a curve. As shown in Figure 9, the vertical axis of the graph represents the number of blog posts and the horizontal axis represents time.

(2) Community Discovery Visualization. Community discovery is a product of person relationship analysis. Through community discovery, people can dig out the relationship between colleagues, classmates, and so on.

(3) Topic Recognition Visualization. The topic identification part is mainly the visualization of topic clustering. It can group blog posts discussing the same or similar things together, making it easier for users to read. Since the categories obtained by clustering cannot be labeled, the system uses keywords to represent the summary of the topic.

(4) Character Recommendation Visualization. The main function of person recommendation is to recommend those users who may be of interest to users. This paper presents three types of recommendation results, including collaborative filtering recommendation, expert recommendation, and attribute similarity recommendation.

3.4. Friend Matching Recommendation Method in the Social Relationship Graph. The relationship in Weibo can be roughly divided into three categories: follower relationship, fan relationship, and mutual fan relationship. Therefore, the available recommendation strategies can be recommended following attention and mutual followers, which

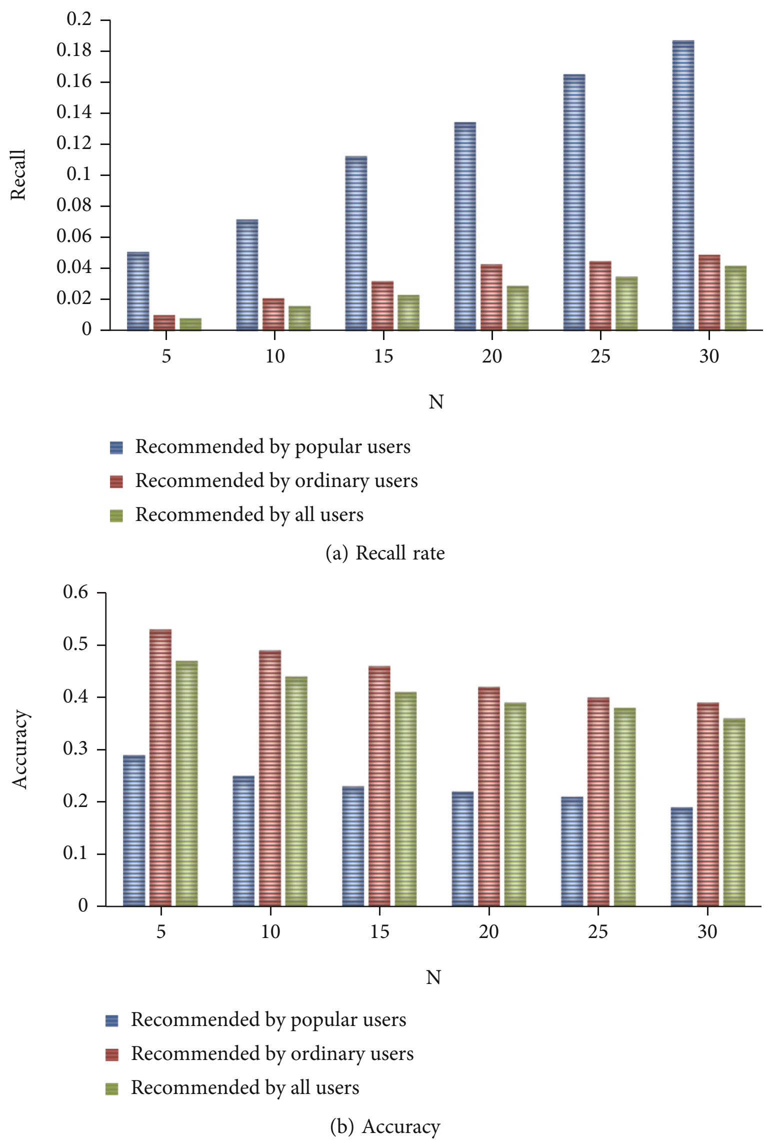


Figure 10: Comparison of sorting accuracy and recall.

are most reflected in the recommendation system of Sina Weibo. However, this recommendation method has a shortcoming that, for example, the recommended attention will rank some celebrities at the top. The mutual fan effect of recommending mutual fans will be much better, because after all, there are still very few people who have mutual fans with celebrities.

For the two friend recommendation strategies proposed above, the main purpose of combining these two algorithms is to reduce the computational complexity and make the whole algorithm more suitable for online use [19]. For example, if a user follows 500 users and recommends friends to these 500 users, the choice of the first recommended candidate is very important. If it is a comparison of all the people on Weibo, the complexity of this algorithm is very high. Therefore, the selected and recommended candidates are generally expanded by one layer of people concerned. Assuming that there are 150000 people after the expansion, the time complexity of the calculation for these 150000 people is greatly reduced. It still takes some time for database operations.

3.4.1. Experimental Data. In order to verify the effectiveness of the above algorithm, this paper uses web crawler to crawl 100 people's social networks and their Weibo information from Sina Weibo. The final crawled data includes character data (30600), basic information (30600), relational data (807370), and Weibo data (2503450). These data are both training datasets and evaluation datasets.

3.4.2. Experimental Strategy. The experiment takes the experimental data crawled above as the dataset and test set. First, each user's attention is partially removed. The recommendation algorithm is used for recommendation, and the recommendation result is compared with the ranking of the deleted part.

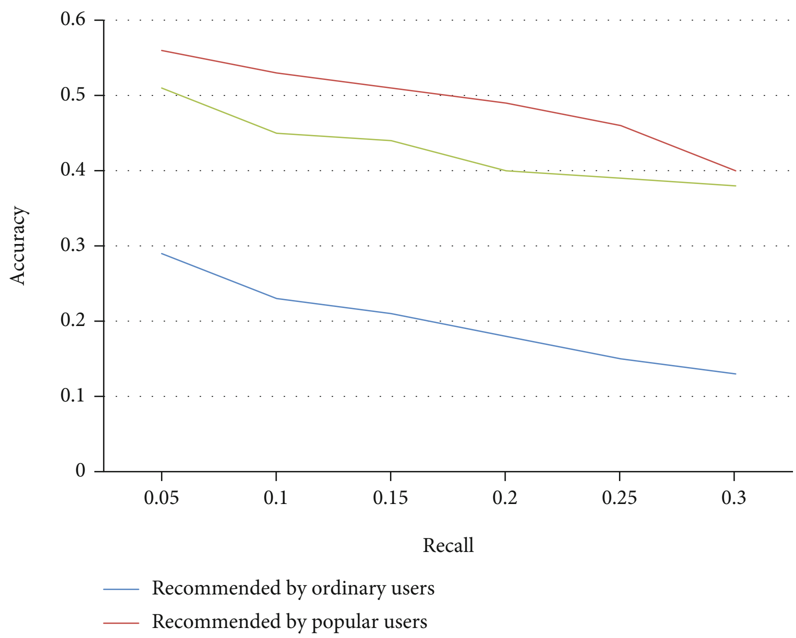


FIGURE 11: Precision/recall curves for three recommendation strategies.

3.4.3. Experimental Results and Analysis. The experimental motivation of this experiment is to demonstrate that recommendation by multidimension is better than recommendation by one dimension. The experiment divides users into three dimensions, the first dimension is popular characters or expert characters (the number of fans is more than 500000 and they are Sina-certified users). The second dimension is ordinary characters except popular characters, and the third dimension is characters in the same school or company [20]. Users are recommended from these three dimensions and then evaluated by the above evaluation indicators.

(1) Experimental Results Recommended by Popular Figures or Experts. This part first selects qualified popular characters or expert characters from the deleted attention list T(u). Similarly, in S(u), the TopN qualified characters to be recommended are selected as the recommended result list and the calculation results are shown in Table 1.

(2) Experiment Results of Common Character Recommendation. This part first selects qualified ordinary people from the deleted attention list T(u) and also selects TopN qualified people to be recommended from S(u) as the recommendation result list. The calculation results are shown in Table 2.

(3) All Characters Recommended Experimental Results. The calculation results of this part are recommended regardless of dimensions, and the common characters and popular characters are mixed together, and the precision rate and recall rate are calculated by the calculation formula of the evaluation index. The calculation results are shown in Table 3.

(4) Result Comparison. The accuracy rate and recall rate of the Top30 recommendation results of the three recommendation strategies are compared, as shown in Figure 10.

It can be seen in Figure 10 that the recommendation accuracy of common characters is significantly better than that of popular characters and all characters. The accuracy rate of popular person recommendation is lower than that of common person recommendation. After analysis, the main reason is that the proportion of popular characters in Weibo is very small. There are about 500 million characters on Weibo and no more than 3 million popular characters. At the same time, from a psychological point of view, most of people's attention to popular characters already exists before they are on Weibo. Most of them will add attention by searching, and the number of stars or experts that a person likes is very limited. After they reach saturation, users will not easily follow other popular characters [18]. Therefore, the recommendation accuracy of popular characters in the table is low. The main reason why the accuracy rate of all character recommendations is lower than that of ordinary characters is also because there are popular characters mixed in. The right side of Figure 11 is the comparison chart of the recall rate. It can be seen that the higher the precision rate, the lower the recall rate. The comparison chart of the precision/recall rate can be observed more intuitively, as shown in Figure 11.

To sum up, the advantages of multidimensional recommendation can be seen, it can avoid the deviation caused by popular characters, and recommending separately is more in line with the user's psychology.

4. Conclusion

With the rapid development of mobile communication technology and Internet technology, people have become inseparable from mobile social products. Mobile social products have become an important way for people to socialize with their mobility and convenience. A large number of social products have emerged on the market. They compete to occupy people's social time from different fields and positioning, and users also get great convenience from them. This paper briefly describes the development history and future trends of social networks and introduces the application status of social relationship graphs in social networks. Then, the method of classifying and recommending users is recommended from two aspects of popular users and ordinary users, which effectively improves the accuracy rate by 21%. Finally, according to this research method, a character analysis system based on the B/S structure is developed. This makes it possible to better verify the usability of the algorithm in the future. The following aspects need to be further studied in the future. There are still many problems in character relationship analysis, such as the analysis of structural holes in the relationship network. The effect of structural holes on network optimization needs further research.

Data Availability

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

Conflicts of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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