Research Article

Chinese Contemporary Music Diffusion Strategy Based on Public Opinion Maximization

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Chinese contemporary music has made tremendous progress in the twentieth century. After entering the twentieth century, with the rise of pop music, Chinese contemporary music has gradually been forgotten by people. Apparently, Chinese contemporary music has a long history and covers huge varieties. Nevertheless, the diffusion of Chinese contemporary music is restricted by many factors. The fundamental reason is that people's cognition of Chinese contemporary music has changed. However, the rise of social networks provides a new opportunity for the diffusion of Chinese contemporary music. By searching nodes with high influence in social networks, where the node is enabled by the sensor, we transform the problem for maximizing public opinion into a process of searching nodes set of maximum influence, thus providing power for the diffusion of Chinese contemporary music. In this paper, from the perspective of percolation, the network connectivity changes caused by node failure are considered, and the set selection problems of high-influence individuals are mapped to the optimal percolation problem when the network has a percolation transition. Then an influence maximization algorithm is proposed based on the network percolation process, and the efficiency of the proposed algorithm is optimized. Through experiments, we can infer the reasonable range of maximum searching times for the influence maximization algorithm. Meanwhile, compared with other baselines, the searching time of the algorithm proposed in this paper is also the least. The experimental results reveal that the proposed algorithm is feasible to diffuse Chinese contemporary music and maximize its public opinion and has a strong impetus for the revival of Chinese contemporary music.

1. Introduction

Any kind of music is inevitable in history. The creation of Chinese contemporary music reflects unique creative elements and concepts in the fast-changing development trend of today's society. With its unique national style and unique charm, it advances continuously, presenting the development trend of modernization and diversification [1–3]. The twentieth century is a multicultural century; the emergence of music is the inevitable result of historical development, so the twentieth-century music creation has also entered a complex, modernized, and diversified new era. In this century, expressionist music, sequential music, collage music, accidental music, electronic music, and many other schools appeared in the West [4, 5]. In the creation, the composer integrates the new music language and music creation techniques, and the new audio-visual music works

emerge at the historic moment. Although China has embarked on a completely different combination of Chinese and Western traditional folk music since the beginning of the twentieth century, it was not until the 1970s and 1980s after the reform and opening-up that mainland China really caught up with the development of modern music. Previously, the Western theory of musical form structure has deeply influenced Chinese music theory. During the period of reform and opening-up, a number of musicians, music educators, and theorists in China fully absorbed Western composition technology theories, concentrated on studying Western music works, and widely learned and accepted Western instruments, bands, and music styles.

Since the 1980s, some composers have made breakthrough explorations of the direction, ideas, methods, and aesthetic concepts of Chinese contemporary music, which have played a positive role in promoting the development of

Chinese contemporary music [6–8]. Chinese contemporary music works seem to have to fill the gaps in many ways and levels. Composers have gradually extended to other artistic directions, such as applying folk music, jazz, and other music from different regions or cultures to their works, using various modern harmony, tone scale, rhythm, and tone color to varying degrees and combining these new materials and techniques with their own creative ideas to create refreshing and diverse styles of music works. To express the content, style, and needs of personalized language, composers freely choose a variety of musical genres.

To some extent, it can be said that the creation techniques of modern music originate from the West, and the musical language is different from the traditional music and aesthetic concepts in China [9]. However, the success of a work must be a perfect combination of various factors, such as times and distinctive national characteristics as well as personal style. In modern music creation, some composers have been exploring and searching for the means and methods to embody Chinese factors and strive to create modern music works with Chinese style, whose fundamental purpose is to create the Chinese atmosphere of the works and provide a "Chinese" background for the works [10–13]. And this Chinese factor is directly reflected in the choice of music creation themes. To pursue the goal of modern music and embody the essence of Chinese culture, composers often directly point out some connection between their works and China in the way of titles and strive to express the content with deep Chinese charm.

As a ritual and music nation with a long culture, the diversity of Chinese music has laid a foundation for the development of Chinese music creation both in content and form. Only by judging and sorting all kinds of data from a multidimensional perspective can the argument be more academic [14]. Under the impact of the new era background, the study of Chinese contemporary music shows strong characteristics of the era. The marketization research of music reflects the productive property of music after the transformation of China's contemporary market economy, and it becomes a commodity that can be profitable in the market. The study of music globalization is urgent to consider the future of Chinese music under the pattern of globalization. Especially, the impact of pop music on modern music makes the diffusion of Chinese contemporary music more and more difficult. Different from tape and CD in the past, today's social networks sweep the Internet, and people are closely connected with others all the time; the diffusion of music seems to become easy, which also provides an opportunity for the diffusion of Chinese contemporary music.

Relying on the Internet, social networks show a rapid development trend, and the advent of email opened the prelude to the development of social networks. Social network platforms such as WeChat and TikTok have shown a rapid development trend relying on the Internet. In social networks, everyone can share their ideas and opinions with others immediately, which not only enriches people's spare time but also promotes information exchange between people [15–17]. The speed at which information

disseminates on social networks is so dramatic that a single piece of information can reach tens of thousands in a short time. As one of the most important problems in social network analysis, influence maximization intends to find high-impact users in the social network [18]. Identifying these high-impact users can provide decision-making assistance for the diffusion of Chinese contemporary music and inject vitality into Chinese contemporary music. The existing methods to measure user influence generally rely on the network topology or define the information propagation model to count the information propagation scope of users under the model, which is mostly based on static networks. However, real social networks tend to change dynamically over time, making it difficult for existing measures to accurately describe users' real influence. In the propagation of Chinese contemporary music, we hope to identify high-influence users in the network and diffuse its propagation.

We describe our contributions as follows:

(1) We apply the influence maximization to the propagation strategy of Chinese contemporary music and find the nodes with the maximum influence, so as to maximize public opinion and diffuse the influence of Chinese contemporary music.

(2) From the perspective of percolation, we consider the network connectivity changes caused by node fault and map the set selection problem of high-influence nodes in influence maximization to the optimized percolation problem.

(3) An influence maximization algorithm is proposed based on the robustness of the network percolation process, and the efficiency of the algorithm is optimized according to the monotonicity of the maximum connected cluster size in the percolation process.

The rest of the paper is structured as follows. In Section 2, we review the related works. An influence maximization algorithm based on site percolation is proposed in Section 3. Experimental results are presented in Section 4, and finally, Section 5 gives the conclusion of this paper.

2. Related Works

2.1. Artificial Intelligence and Music. As technology for simulating, extending, and expanding human intelligence, artificial intelligence has been advanced from the primary form of computational intelligence to the advanced form of perceptual intelligence and cognitive intelligence [19–22]. Music is one of the reappearance forms of human emotion and cognition, and artificial intelligence technology has gradually penetrated into every link of music diffusion. In the narrow sense, music information refers to the inner artistic information that is composed of a group of interrelated and meaningful musical symbols and can express some complete meaning. Generalized music information also includes external data information such as music carrier, music copyright, and music user preference. The participation of artificial intelligence in the process of music

information collection can be divided into two parts: one is the collection of physical music information [23–25]. For example, music information retrieval (MIR) extracts audio features based on audio signal processing and extracts music information from the audio content. The other is the collection of music external carrier, copyright, and user preference information.

AI music generation platform uses genetic algorithm [26], neural network [27], Markov chain [28], and hybrid algorithm [29] technology to make rules for the computer, in the process of deep learning of large-scale music library analysis of composition rules and other music information for re-creation, so as to achieve independent composition, lyrics, and other music creation functions.

2.2. Influence Maximization. Music should be shared, as well as Chinese contemporary music. With the popularization of pop music, Chinese contemporary music is gradually forgotten. How to share Chinese contemporary music with more people and maximize the diffusion of influence is the main content of influence maximization. Information in social networks is generated by individuals and then disseminated along the edges between individuals. Influence refers to the phenomenon that individuals' opinions and information on the network influence others and eventually form a cascade of information transmission. In [30], the authors introduced the issue of maximizing multiple influences across multiple social networks, that is, influential users could accept multiple products for free, while influential users had sufficient purchasing power to use multiple promotions in their social interactions. The existing influence diffusion model does not consider overexposure; in [31], the authors proposed the influence diffusion model to capture overexposure and studied the problem of maximum influence under the independent cascade model of delay perception with overexposure. In [32], the authors presented an effective method to maximize the influence in signed networks, so as to maximize the positive influence diffusion in signed networks. In [33], the authors proposed a problem of maximizing efficiency considering the influence of diffusion delay. In [34], the authors proposed a practical algorithm for adaptive influence maximization and a general framework that can be instantiated by any existing nonadaptive influence maximization algorithm with expected approximation guarantees.

However, to the best of our knowledge, few scholars have studied the diffusion strategies of Chinese contemporary music. Therefore, we introduce the maximization of influence into the diffusion strategy to find the nodes set with the biggest influence, so as to maximize public opinion and diffuse the Chinese contemporary music.

3. Influence Maximization Algorithm Based on Site Percolation

The removal of some nodes and the edges connected to them from the network is called percolation, more accurately, site percolation. Percolation can be used as a model for many

real-world phenomena, such as router failures on the Internet, traffic jams in urban road networks, and species extinction in the food web. One of the purposes of studying percolation is how node failure affects the whole network operation. It is very important to identify the nodes that have a great influence on the function of the network system. By diffusing the influence range of these nodes, Chinese contemporary music can be widely replayed.

Most nodes in the network are connected to form a large branch without removing or removing only a small number of nodes. As percolation proceeds, when the removal ratio of nodes reaches a certain value, the network will split into several small branches, which is called percolation transition [35]. The percolation threshold is the core content of percolation research and is of great significance for network control and network robustness research. Percolation provides a natural model for the study of network robustness, but the percolation threshold is not the only important parameter. Because most nodes of the network have failed when the percolation threshold is approached, another important aspect of studying percolation is to observe how the maximum connected subgraph size of the remaining network changes with the removal of nodes. The size of the maximum connected subgraph indicates that at least most of the networks are in normal operation. Therefore, this subsection selects the relative size of the maximum connected subgraph to study the robustness of the network.

3.1. Problem Definition. The problem of this paper can be specifically described as how to remove nodes in the network to minimize the robustness of the remaining network, that is, to maximize the impact on the structure and function of the network. The idea is that the robustness of the percolation algorithm is affected by the relative size of the maximum connected subgraph of the network. To minimize the robustness of the network, the nodes added each time should minimize the growth rate of the maximum connected cluster size of the network in the process of restoring the entire network from the empty network, while how to make the largest connected cluster in the network grow slowly becomes our concern. To merge clusters and update the maximum connected cluster size, two conditions need to be met: (i) the node to be added has a neighbor node and the neighbor node has been added to the network and (ii) the cluster number of the node to be added is different from that of the neighbor node.

If updating the maximum connected cluster size is to be avoided as much as possible, it can be obtained from condition (i) that the number of neighbor nodes of the added node should be as small as possible or the neighbor nodes have not been added to the network. According to condition (ii) and the cluster combination rule, the cluster number of all neighbor nodes of the added node should be the same as far as possible. To sum up, it can be inferred from the above that the node selection rule of recovering the whole network from an empty network is as follows: (a) the number of neighbor nodes should be as small as possible and (b) the neighbor node has not been added to the network or the

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Input: G(V, E), Q
Output: Q_opt
(1) initialize R = R(V, E), V(R)←∅, E(R)←∅
(2) Q_opt ←— ∅
(3)    while Q ≠ ∅ do
(4)        find u←arg min d(V(R) ∪ {v})
(5)        add node u and its corresponding edges to network R
(6)        Dequeue (Q, U)
(7)        Enqueue (Q_opt, U)
(8)    end while
(9) return Q_opt
```

ALGORITHM 1: Influence maximization algorithm based on site percolation.

```
Input: G(V, E), Q
Output: u
(1) k ←— 0
(2) sort queue Q by d(V ∪ {v})
(3)    for k ≤ m do
(4)        v_k = kth node in Q
(5)        calculate d(U ∪ {v_k}) and update d(U ∪ {v})_min
(6)        k = k + 1
(7)        if d(U ∪ {v})_min ≤ d(V ∪ {v_{k+1}})_min
(8)            break
(9)        end if
(10)   end for
(11) return u in d(U ∪ {v})_min
```

ALGORITHM 2: Node optimal search algorithm.

cluster number of all neighbor nodes should be the same as possible.

Rule (a) indicates that the centrality measure most directly related to the growth rate of the maximum connected cluster size is the degree of nodes. The higher the degree of the node is, the faster the size of the maximum connected cluster grows after the node is added. Therefore, an initial queue Q can be constructed according to the degree of the node. Each time, a node with the lowest degree is selected from the network and added to the queue Q, and each node added must be removed from the network, and all remaining nodes are reordered according to the degree value until all nodes are added to the queue Q. Then, according to rule (b), a node that minimizes the change of the largest connected cluster size is selected from the sequence every time.

3.2. Influence Maximization Algorithm.

Let $N(R)$ represent the node set in network R and $C(N)$ represent the size of the largest connected cluster in network R. Given social network $G(V, E)$, where V represents the set of nodes and E represents the set of edges. How to find K initial users so that information can be disseminated through these initial users and the number of affected users can reach the maximum, that is

TABLE 1: Experimental data sets.

	socfb-Caltech36	socfb-UC61	Rovira i Virgili	WordNet
N	796	13,746	1,133	146,005
M	16,656	442,174	5,451	656,999
K	43.32	64.33	9.62	9.001
C	0.408	0.261	0.165	0.097

$$D' = \arg \max \sigma(D), \tag{1}$$

where D represents the initial user set, $\sigma(D)$ represents the number of affected users, $D \subseteq V$, and $|D| = K$.

The influence maximization algorithm is shown in Algorithm 1.

Assuming that the time complexity for adding nodes is $O(N)$ and the time complexity for adding edges is $O(M)$. The most time-consuming part of Algorithm 1 is the process of finding the maximum connected cluster size with the minimum change. Every time an optimal node u is found in the whole algorithm process, its $d(V \cup \{v\})$ is no longer calculated in the subsequent search process. The whole process is equivalent to make $N/2$ percolation, so the time complexity of the whole algorithm is $O(N^2 \log N + NM)$. The whole process calculates $N(N+1)/2$ $d(V \cup \{v\})$ twice in
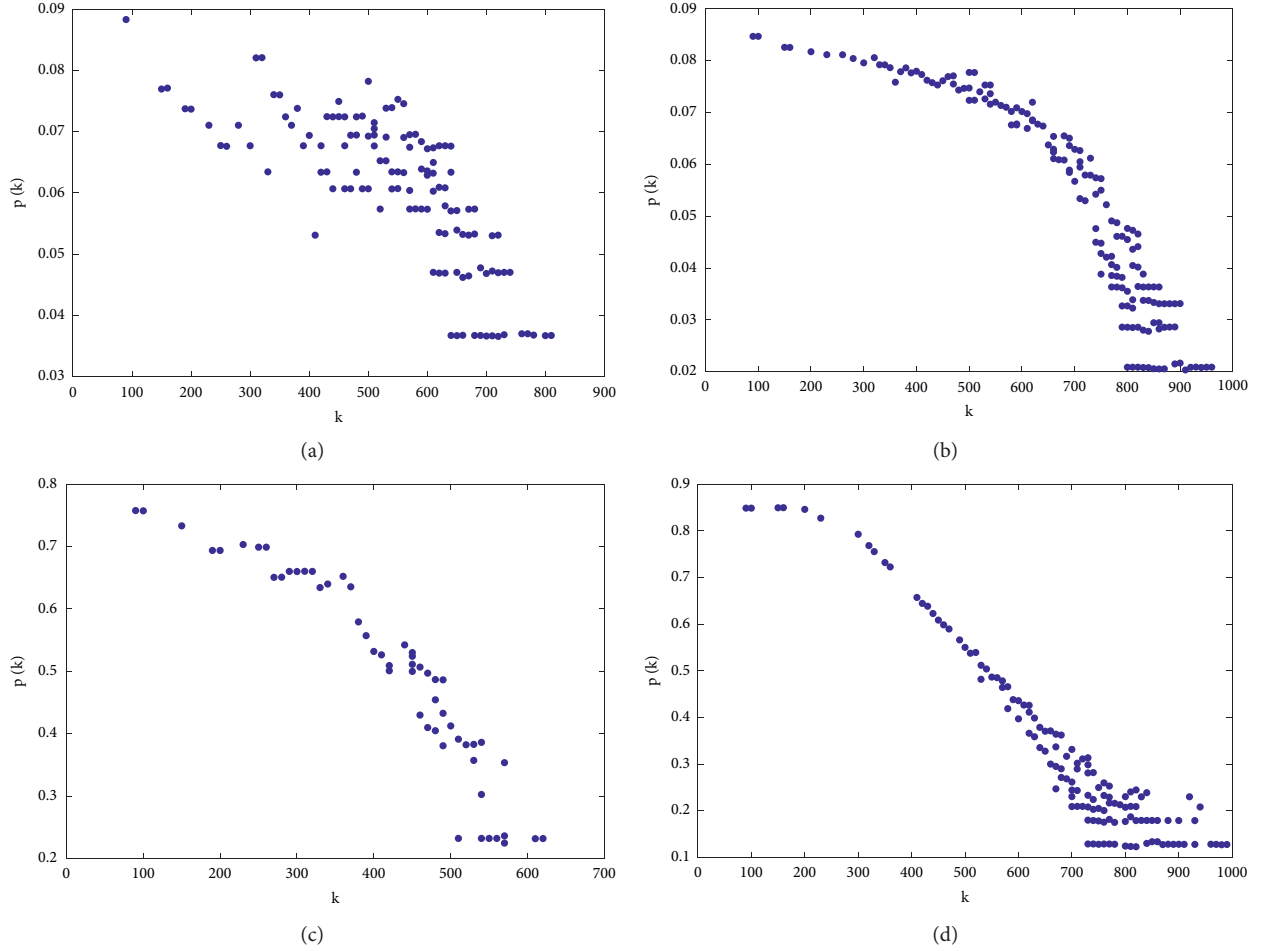
Figure 1: Node degree distribution of four data sets: (a) socfb-caltech36 data set, (b) socfB-UC61 data set, (c) Rovira i Virgili data set, and (d) WordNet data set.

total, and the average time complexity of calculating $d(V \cup \{v\})$ is $O(\log N + M/N)$.

3.3. *Optimization of Algorithm Efficiency.* When nodes are added to network R, the size of the maximum connected cluster either increases or is unchanged. Apparently, $d(V)$ is monotonically increasing and non-negative, that is

$$d(V \cup \{v\}) \geq d(V). \tag{2}$$

Then the following inequality is easily proved to be true:

$$\forall V \subset U \subset N, \forall v \in N, v \notin U, d(V \cup \{v\}) \leq d(U \cup \{v\}). \tag{3}$$

Equation (3) can be used to draw the following conclusions.

The size of the largest connected cluster in the network after adding node v can only increase or remain the same with each iterative calculation for any node v, which means that the size of the largest connected cluster in the network after adding node v in this iterative calculation can be used as the lower limit of the next iterative calculation.

To find the node in the queue that minimizes the change of the largest connected cluster size, the algorithm can be reduced, and the search efficiency can be improved by

applying the above conclusions and setting the maximum search times. The specific implementation method is as follows.

Before each iterative calculation, the calculation results of the previous iteration shall be sorted from small to large as the lower limit of the iterative calculation, and the nodes shall be evaluated in this order. For each node evaluated, the minimum value of the maximum connected scale of the network must be updated. If the minimum of the maximum network connected scale after a node is added is less than or equal to the lower value of the next node to be evaluated or reaches the maximum search times, the search can be stopped. Since under the premise of not exceeding the maximum search times, the node that causes the minimum change of the maximum connected scale of the network has been found.

The node optimal search algorithm is shown in Algorithm 2. The most time-consuming part of the algorithm is to calculate the maximum network connected size $d(U \cup \{v_k\})$ after node v_k is added. According to Algorithm 1, the average time complexity of $d(U \cup \{v_k\})$ is $O(\log N + M/N)$. Since the number of searching optimal nodes per time does not exceed m, the average time complexity of the optimal search algorithm does not exceed
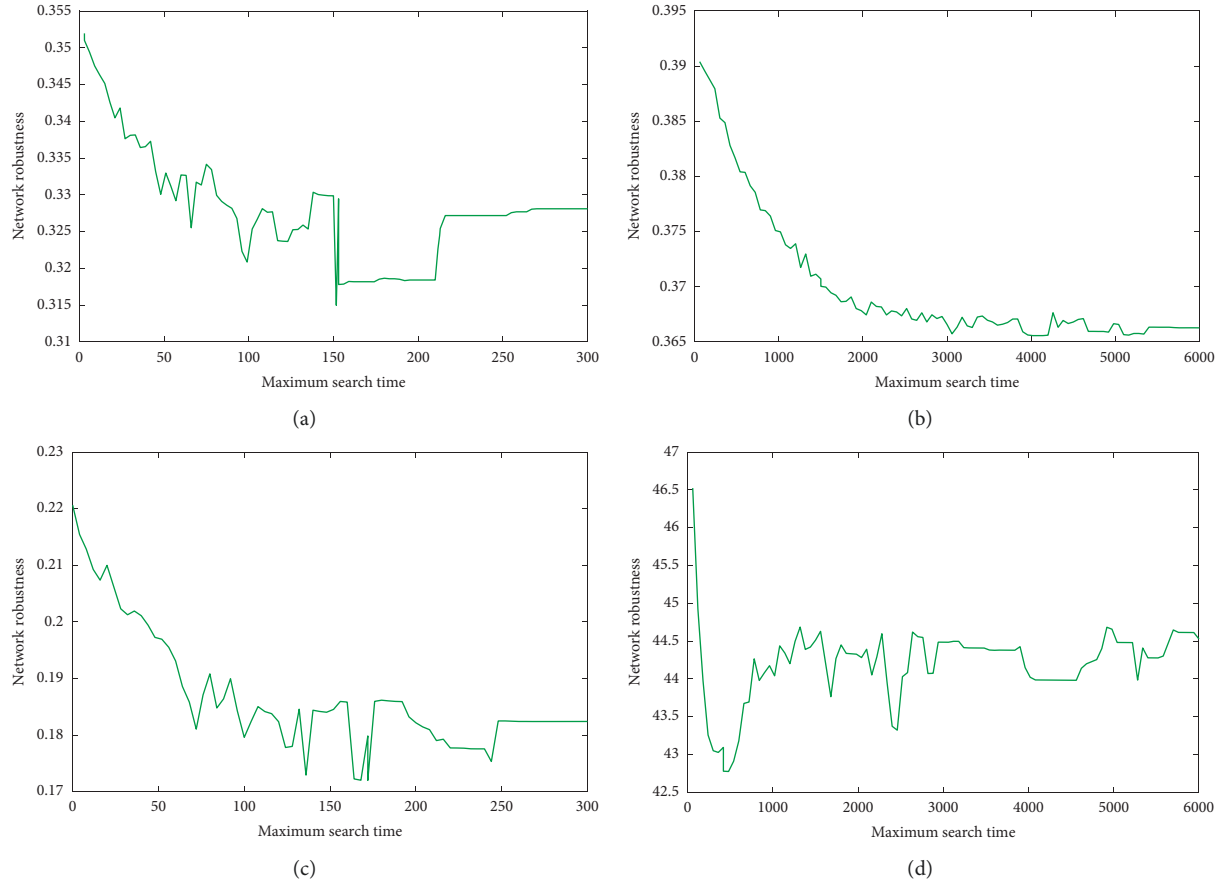
(a)

(b)

(c)

(d)

FIGURE 2: Change of network robustness with a maximum number of search times: (a) socfb-caltech36 data set, (b) socfB-UC61 data set, (c) Rovira i Virgili data set, and (d) WordNet data set.

4. Experiments

4.1. Setup. The experimental data set and its basic attributes are shown in Table 1, where N is the total number of nodes in the network, E is the total number of edges in the network, K is the average degree of the network, and C is the average clustering coefficient. Socfb-caltech36 and SocfB-UC61 data sets in Table 1 are social networks extracted from Facebook, where nodes in the network represent users, and edges represent friend relationships between users. Rovira i Virgili is the e-mail communication network of the University of Tarragona in Spain, where nodes in the network represent users and edges indicate that at least one e-mail has been sent between users. WordNet is the vocabulary network in the WordNet data set, where nodes in the network represent English words and edges represent the relationships between them, such as synonyms and antonyms [36]. In real life, there are many large-scale complex networks, such as Internet, social networks, transportation network, biological network, and so on. In the beginning, the degree distribution of these complex networks is Poisson distribution. For social networks, the degree of each node obeys the power law

$O(m \log N + mM/N)$, and the average time complexity of the influence maximization algorithm does not exceed $O(m \log N + mM/N)$.

distribution. Most common nodes have few connections, and a few popular nodes have many connections. Such networks are called scale-free networks. We plotted the node degree distributions of the above four data sets to observe their scale-free characteristics. The node degree distribution is shown in Figure 1, where $p(k)$ is the proportion of nodes with degree k in the entire network. The data of socfb-Caltech36 and Rovira i Virgili data sets are relatively sparse, resulting in insignificant scale-free characteristics. The tail of socfB-UC61 and WordNet data sets generally obey the power law distribution, and their power law index is between 2 and 3, showing obvious scale-free characteristics. Therefore, we selected two obvious scale-free data sets and two non-obvious scale-free data sets as experimental data sets.

4.2. Algorithms in Comparison. Since the effect of the influence maximization algorithm is affected by the maximum number of searches m, different m is selected for further test on the four data sets to observe the influence of the maximum number of searches m on the network robustness. Experimental results of the network robustness of the four data sets varying with the maximum search times m are shown in Figures 2(a)–2(d). The curve in the figure represents the variation curve of network robustness with the maximum search times m. It can be seen from Figures 2(a)–
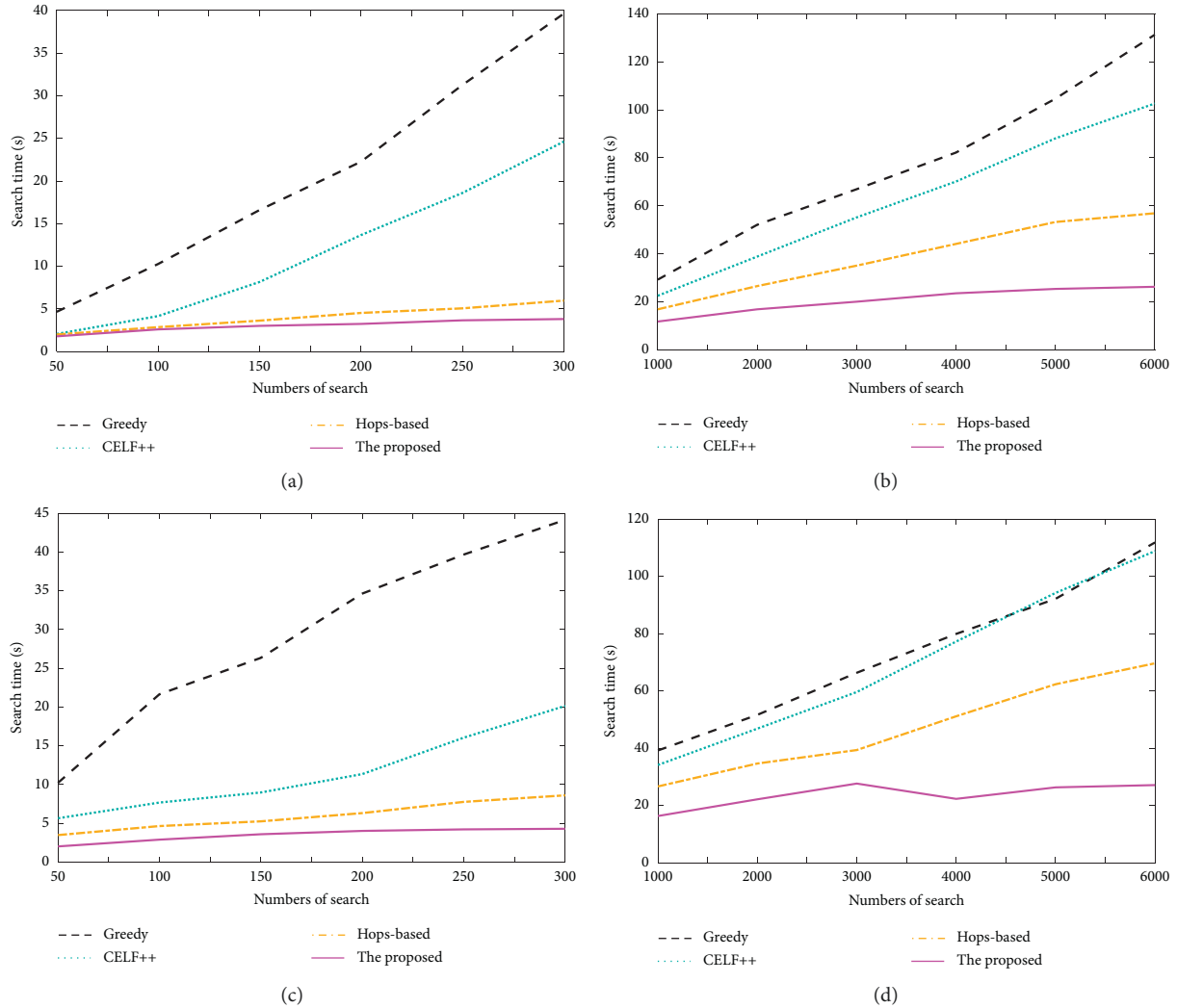
FIGURE 3: Search time: (a) socfb-caltech36 data set, (b) socfB-UC61 data set, (c) Rovira i Virgili data set, and (d) WordNet data set.

2(d) that with the increase of the maximum search times m, the network robustness tends to decline and becomes stable after a certain degree of decline. Therefore, we can infer that the reasonable value range of parameter maximum search times m of the influence maximization algorithm is between $[0.1B, 0.2B]$, where B is the number of nodes in the network.

Search time is another important metric to verify the effectiveness of the algorithm and plays an important role in the diffusion of Chinese contemporary music. We compare search time with three classical influence maximization algorithms, namely greedy algorithm, CELF++ algorithm, and Hop-based influence estimation algorithm. As can be seen from Figures 3(a)–3(d), the comparison of search time on the four data sets shows that with the increase in search times, the influence maximization algorithm based on site percolation proposed in this paper has the slowest increase in search time and gradually converge after a certain number of times, and the search time is always the least. This is because the introduction of percolation reduces the search time by about half. The greedy algorithm can give a better

solution set, but its time complexity is too high. CELF++ algorithm rearranges the nodes according to their size before each reassessment of the node's marginal gain. Each node is evaluated, and the maximum marginal gain is updated. However, Monte Carlo simulation is still used when evaluating the node's marginal gain. A large amount of time consumption makes it difficult to apply to large-scale social networks, so the search time is also longer.

5. Conclusion

Although Chinese contemporary music has been gradually forgotten after a hundred years of development, the rise of social networks provides a new opportunity for its diffusion. We design an influence maximization algorithm based on percolation mode and optimize the efficiency of the algorithm. Since the scale-free network has robustness under random failure, the problem of set selection of high-influence individuals in influence maximization can be transformed into a problem of network percolation, and the

advantages and disadvantages of the selected nodes set can be evaluated with network robustness, thus pointing out the direction for the diffusion of Chinese contemporary music. To minimize the robustness of the network, the node that increases the scale of the current maximum connected subgraph slowest can be selected each time in the percolation process. Therefore, the more backward the node is, the higher its influence will be. In the process of nodes selection, the searching efficiency of the proposed algorithm can be improved by increasing the size of the maximum connected subgraph. The experimental results reveal that the proposed influence maximization algorithm based on site percolation can search the nodes set of influence maximization with very little search time, which has strong theoretical support for the diffusion of Chinese contemporary music.

Although this paper has made some progress in the study of the maximization of influence of Chinese contemporary music diffusion, it is undeniable that there are still some deficiencies in the work. Several directions in the future are still worthy of further exploration and research:

(1) As the scale of data in different time periods is generally different and it is difficult to ensure the comprehensiveness of data during data collection, the length and quantity of network snapshots will have a certain influence on experimental results. To avoid or reduce the interference of these non-experimental factors, more analysis on data set processing is needed in future work.

(2) The main reason why the calculation results of the existing information diffusion model differ greatly from the real social network is that the probability of information diffusion among users depends on many uncertain factors such as people's interests and intimacy between people, and the influence of users in different fields and events is also different. Therefore, in order to truly reveal the influence of users, it is necessary to further study the probability of information diffusion among users.

(3) Chinese contemporary music has a long history and is an important part of Chinese culture. With the rapid development of the economy and science and technology, all walks of life have encountered unprecedented opportunities and challenges. In the era of new media, the diffusion and development of Chinese contemporary music have also faced new changes. Under such circumstances, Chinese contemporary music has encountered development bottlenecks both in content and form but has new opportunities in diffusion. Excellent Chinese contemporary music can make use of the characteristics of the times and new media to promote its vigorous development. The diffusion path of Chinese contemporary music in the new media era is characterized by diversification. In view of the current situation of the development of Chinese contemporary music, we should take advantage of the opportunities brought by new media and adopt various ways to diffuse Chinese contemporary music around the world.

Data Availability

All data used to support the findings of the study are included within this article.

Conflicts of Interest

The author declares that there are no conflicts of interest in this article.

Acknowledgments

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