Influence Minimization Algorithm Based on Coordination Game

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ABSTRACT Influence analysis is the basic technology for predicting potentially hazardous behavior and determining the traceability of the hazardous behavior in the public security domain. Previous research has focused on maximizing the diffusion of the influence; however, little research has been performed on the method of minimizing the influence of negative information dissemination in networks. This paper proposes an influence minimization algorithm based on coordinated game. When the negative information is generated in the network and some initial nodes have been infected, the goal is to minimize the number of the final infected nodes by discovering and blocking the $K$ uninfected nodes. First, the algorithm assumes that the behavior of the node propagating information depends on the coordination game with its neighboring nodes. Second, based on the local interaction model between the nodes, this paper quantifies the level of the influence of a node that is affected by its neighbors. Finally, the heuristic algorithm is used to identify the approximate optimal solution. The results of experiments performed on four real network datasets show that the proposed algorithm can suppress negative information diffusion better than the five considered existing algorithms.

INDEX TERMS Social network, influence minimization, coordination game, negative information

I. INTRODUCTION

Currently, social networks have become an important platform for information dissemination. With criminal behavior moving from offline to online domains, many potential criminals try to increase their harmful influence via various social media platforms and later spread inductive speech opinions to wider audiences to mislead the public opinion. Based on the current situation, preventing and reducing cybercrime has become one of the primary strategic tasks of the related law enforcement agencies. Influence analysis technology, as one of the most important technical means in the prevention of cybercrime and the foundation of mining group behavior patterns, possesses extremely broad application prospects in the public security area and many other fields. Simultaneously, the influence analysis of the social network can be used as a basic research technique to analyze topic evolution in social networks, social behavior characteristics, information dissemination models and many other issues. Therefore, research related to the influence analysis is valuable and necessary.

The social influence is a phenomenon in which the users’ behaviors and thoughts are modified by others, and this phenomenon has a wide range of application scenarios in real networks of the actual world. In recent years, many scholars have conducted a series of studies on maximizing the social influence. Relevant scholars have investigated the maximization of the subject perception influence and attempted to find $K$ seeds from the social networks, given the maximum perceived influence of the topic. In light of the current situation in which most of the existing studies are oriented to the static network structure, some scholars have conducted an influence analysis on dynamic networks. Some scholars have studied the time aware influence maximization model to impose time constraints on the influence diffusion process. Furthermore, from the perspective of the coordination game, some scholars described the reality of the spread of information. More often than not, the value of the influence maximization research is reflected in scenarios, such as online marketing and advertising. However, in terms of the spread of harmful information, such as negative influences and malicious rumors in the network, only a few scholars have focused on the minimization of the associated negative effects. Consider
the spread of negative information as an example; even if a small percentage of people in the network are affected at the initial stage, the user group affected in the network will expand tremendously through the network diffusion mechanism\cite{21,22,23}. Therefore, determining approaches to reduce the spread of the negative information in the network could be a research direction of considerable practical significance. Currently, some scholars have performed relevant research in the field of influence minimization. B Wang et al.\cite{22} proposed a dynamic rumor influence minimization model based on the user experience and conducted related comparative test experiments on the real world SinaWeibo social network data set. S Wang et al.\cite{23} utilized the real email communication network data set and minimized the number of the ultimately contaminated users by identifying and blocking the uninfected users. Q Yao et al.\cite{24} proposed a greedy algorithm with a high precision and two effective heuristic algorithms to minimize the number of the final infected users by blocking K links. L. Fan et al.\cite{25} studied the rumor blocking problem in the social networks and proposed the concept of a “protector”, which could inhibit the spread of rumors in a network by initiating a cascade of protective links.

In contrast to previous work, this paper proposes an influence minimization algorithm based on coordinated game (IMCG). The core idea of this approach is that the interconnected individuals tend to make the same decision; when an individual makes a change, the individual with whom it is linked might make the same change to seek coordination for the benefits of both parties. In addition, based on the phenomenon that the network nodes are interrelated by relying on relatively long-lasting social relationships, this paper quantifies the level of influence of the nodes to their neighbor nodes by studying the interaction patterns among the network nodes. Eventually, the diffusion spread of the negative information is minimized by blocking a limited number of nodes in the network. Section 2 of this paper defines and explains the influence minimization algorithm based on coordinated game. Section 3 presents the relevant pseudocode for the proposed algorithm. Section 4 compares six algorithms on four public real network datasets, and the results demonstrate the effectiveness of the proposed algorithm. Section 5 presents the conclusions of this paper.

II. The Framework of the Influence Minimization Algorithm Based on Coordination Game

The proposed IMCG algorithm is based on the following concepts: First, a coordination game model among the nodes is constructed, and the decision made by the nodes depends on the game interaction of the nodes with their corresponding neighbors. Simultaneously, to solve the critical defects in the previous research: the strategic benefits of each node are obtained through random allocation. This paper quantifies the value of the benefit space in the coordinated game model by considering three local interaction models. From the perspective of sociology, we construct a local interaction model based on the principle of distance dynamics. It is assumed that any node in the network will interact with other nodes, and the interaction will change the distance between the nodes to quantify the level of influence of a node that is affected by its neighbors. Finally, we define a method for finding the seed sets in the influence minimization model. This model determines whether the nodes in the network will be infected under the influence of its infected neighbor nodes, based on the node strategic choice, which is defined in the coordination game model. Subsequently, the algorithm determines the seed nodes to be blocked to suppress the spread of negative information.

A. Coordination Game Model

Interconnected individuals have a tendency to make identical decisions. When an individual makes a change, the individual with whom it is linked may make the same change\cite{19,20}. Based on this concept, we build a basic coordination game model, as shown in FIGURE 1: Assuming there exist two individuals \( u \) and \( v \), both will choose from between strategies 1 and 2, and the benefits are defined as follows:

1) Both \( u \) and \( v \) adopt strategy 1; consequently, \( u \) and \( v \) obtain the benefits of \( i_{u1} \) and \( i_{v1} \).
2) Both \( u \) and \( v \) adopt strategy 2; consequently, \( u \) and \( v \) obtain the benefits of \( i_{u2} \) and \( i_{v2} \).
3) Both \( u \) and \( v \) adopt different strategies; consequently, \( u \) and \( v \) do not obtain the benefits.

**FIGURE 1. The Benefit Matrix of the Coordinating Game**

Extending this principle to the social networks, all the nodes will choose between two strategies, namely, propagating (Y) or not spreading (N), when faced with the choice of whether to propagate a certain message. The nodes in the network may be linked to multiple nodes; however, different neighbor nodes have different level of influences. Thus, the following basic definitions are given:

**Definition 1 Benefit Space:** Given a network structure, \( G = (V, E, i) \) is an undirected graph, \( V \) is the set of nodes, \( E \) is the set of edges, and \( i \) is the benefit space, where \( |i| = 2|E| \). In addition, \( \exists e = (u, v) \in E \). When the node \( u \) adopts a strategy, it will obtain different benefits: \( I_{uvY} \) or \( I_{uvN} \). The benefit space has the following characteristics: \( \forall i_{uv} \in i, i_{uv} = \{i_{uvY}, i_{uvN}\} \).
The benefit space describes the potential amount of benefits that one node in the network may obtain when interacting with the different neighbor nodes in the game: \( i_{uv} = \{i_{uvY}, i_{uvN}\} \). We present the game interaction strategy between nodes \((u, v)\) as Definition 2. Considering the choice of strategy between propagating \((Y)\) and not spreading \((N)\), there exist three different possibilities that \(u\) and \(v\) might adopt: \(Y, Y, N\), and \(N N\). These three different possibilities determine the amount of benefits that \(u\) and \(v\) can obtain.

**Definition 2 Game Strategy:** Assume the nodes \(u, v \in V\), \(\exists e = \{u, v\} \in E\). The benefits obtained by nodes \(u\) and \(v\) are defined as follows. The game strategy of IMCG is shown in FIGURE 2.

1. Both \(u\) and \(v\) adopt strategy \(Y\); consequently, \(u\) and \(v\) obtain the benefits of \(i_{uvY}\) and \(i_{vuY}\).
2. Both \(u\) and \(v\) adopt strategy \(N\); consequently, \(u\) and \(v\) obtain the benefits of \(i_{uvN}\) and \(i_{vuN}\).
3. Both \(u\) and \(v\) adopt different strategies; consequently, \(u\) and \(v\) do not obtain benefits.

**FIGURE 2. The Game Strategy of the IMCG**

The game strategy indicates the amount of benefits that two nodes \((u\) and \(v\)) can obtain under the three different possibilities. Considering that there might be multiple neighbor nodes of one node in the social network, the decision made by the node depends on the results of the coordination game with all its neighboring nodes. In Definition 3, we quantitatively describe the reason any node \(u\) in the network makes the strategic decisions.

**Definition 3 Strategic Choice:** Consider a network structure \(G\). The total benefit \(l_u\) of node \(u\) is defined as the sum of the benefits obtained after participating in the coordinating game with all its neighbor nodes \(U(u) = \{v \in V | \{u, v\} \in E\}\). Assuming that the node obtains the total benefits \(l_{uY} > l_{uN}\) when the strategy \(Y\) is chosen, the node will select the strategy \(Y\), and vice versa. Assume that node \(u\) knows all the strategic choices of its neighbors, \(U_{uY}\) is the set of neighbors that select strategy \(Y\), and \(U_{uN}\) is the set of neighbors that select strategy \(N\). When equation (1) is satisfied, node \(u\) will select strategy \(Y\).

\[
\sum_{v \in U_{uY}} i_{uvY} > \sum_{v \in U_{uN}} i_{uvN} \tag{1}
\]

Negative information is generated in the social networks, and some initial nodes are infected. These uninfected nodes will follow the strategy of the coordinated game model to decide whether to spread the negative information or not. When most of the neighbor nodes of an uninfected node \(u\) have been infected, satisfying equation (1), node \(u\) will make a decision to propagate the negative information, and it will subsequently be infected.

**B. Local Interaction Model**

In real networks, the benefits in the benefit space may not be consistent. Therefore, a local interaction model based on the principle of distance dynamics\(^{26}\) is constructed to further quantify the benefit space.

**Definition 4 Neighbors of node \(u\):** Given a network structure \(G\), \(\forall u \in V\). The neighbors of node \(u\) are defined as \(U^*(u)\):

\[
U^*(u) = \{v \in V | \{u, v\} \in E\} \cup u \tag{2}
\]

Next, the number of co-neighbor nodes is considered among the interconnected nodes to measure their similarity. \(\forall e = \{u, v\} \in E\); thus, a larger number of co-neighbor nodes between node \(u\) and \(v\) corresponds to a greater structural similarity. If both nodes have approximately the same network topologies, the two nodes have similar functions to some extent, and the mutual influence is larger. When one of the nodes makes a strategic choice, the other node is more likely to be affected by the node.

**Definition 5 Node Similarity:** Given a network structure \(G\), the similarity \(s(u, v)\) between two nodes \(u\) and \(v\) is shown in equation (3), where \([U^*(u)]\) is the number of nodes in \(U^*(u)\):

\[
s(u, v) = \frac{|U^*(u)| + |U^*(v)|}{\sqrt{|U^*(u)| \times |U^*(v)|}} \tag{3}
\]

The node similarity \(s(u, v)\) provides an intuitive technique to characterize the similarity of nodes. The similarity in the network topology determines the level of similarity between the two nodes. The nodes are related to each other by relying on relatively long-lasting social relationships. The node similarity \(s(u, v)\) is used as the initial state. Under the action of the “common consciousness” and “common values”, the changes will occur in three different situations, as shown in FIGURE 3, FIGURE 4, and FIGURE 5. In the following section, we explain the influence of the three interaction modes on the similarity.

**Interactive Behavior 1: The Influence of the Directly Connected Nodes**

As shown in FIGURE 3, the similarity \(s(u, v)\) between nodes \(u\) and \(v\) in the network is changed by the interaction of its directly connected nodes \(u\) and \(v\). The nodes attract each other under the influence of the “common consciousness” and “common values”, which leads to an increase in the similarity \(s(u, v)\) between nodes \(u\) and \(v\).
To quantify the influence of the directly connected node interaction, $DI$ is defined as in equation (4). Here, $\sin$ is a sine function, and $\text{deg}(u)$ is the degree of node $u$.

$$DI = \frac{\sin(s(u,v))}{\text{deg}(u)} + \frac{\sin(s(u,v))}{\text{deg}(v)}$$

(4)

Interactive Behavior 2: The Influence of the Common Neighbor Nodes

The common neighbor nodes of nodes $u$ and $v$ are defined as $CN = (U(u) - u) \cap (U(v) - v)$. Since the common neighbor nodes are simultaneously connected to nodes $u$ and $v$, the common neighbor nodes change the similarity $s(u, v)$ between the nodes $u$ and $v$. Specifically, as shown in FIGURE 4, each common neighbor node attracts nodes $u$ and $v$ to move toward itself, resulting in an increase in the similarity $s(u, v)$.

To quantify the influence of the interaction of the common neighbor nodes, $CI$ is defined as in equation (5):

$$CI = \sum_{z \in EN(u)} \left( \frac{1}{\text{deg}(u)} \sin(s(u,z))s(v,z) \right)$$

$$+ \left( \frac{1}{\text{deg}(v)} \sin(s(v,z))s(u,z) \right)$$

(5)

Interactive Behavior 3: The Influence of the Exclusive Neighbor Nodes

The exclusive neighbor nodes of nodes $u$ and $v$ are defined as $EN(u) = U(u) - U(u) \cap U(v)$ and $EN(v) = U(v) - U(u) \cap U(v)$. As shown in FIGURE 5, each exclusive neighbor node of the node draws the node closer to itself. Thus, under the joint action of the exclusive neighbor nodes of nodes $u$ and $v$, the trend of $s(u,v)$ is unknown. To investigate the change in the similarity $s(u,v)$, we study whether each exclusive neighbor node of node $u$ is similar to node $v$, and vice versa. If the exclusive neighbor node of node $u$ is similar to node $v$, the movement of node $u$ to the exclusive neighbor node will result in an increase in the similarity $s(u,v)$. Similarly, if the exclusive neighbor node of node $u$ is not similar to node $v$, the movement of node $u$ to the exclusive neighbor node will result in a decrease in the similarity $s(u,v)$. Therefore, the parameter $\lambda$ is introduced.

$$\rho(u, z) = \begin{cases} s(v,z) & s(v,z) \geq \lambda \\ s(v,z) - \lambda & s(v,z) < \lambda \end{cases}$$

(6)

$\rho(u, z)$ characterizes the level of positive or negative influence on the similarity $s(u,v)$.

Subsequently, to quantify the influence of the interaction of the exclusive neighbor nodes, $EI$ is defined as in equation (7):

$$EI = \sum_{z \in EN(u)} \left( \frac{1}{\text{deg}(u)} f(s(u,z))\rho(u,z) \right)$$

$$+ \sum_{z \in EN(v)} \left( \frac{1}{\text{deg}(v)} f(s(v,z))\rho(v,z) \right)$$

(7)

Finally, we consider the three interaction modes together and define the similarity $S'(u, v)$ between nodes $u$ and $v$ as

$$S'(u, v) = s(u,v) + DI + CI + EI$$

(8)

This paper assumes that $i_{uv} = i_{uv}^\ast$, and the size of the final benefit space satisfies equation (9):

$$i_{uv} = \frac{S'(u,v)}{\text{deg}(u)}, i_{vu} = \frac{S'(u,v)}{\text{deg}(v)}$$

(9)

C. Influence Minimization Model

The paper defines the influence minimization model as follows. Given a network structure $G$, it is assumed that the negative information appears in the network and infects some initial nodes: $T \subseteq V$. The goal of the model is to minimize the spread of the negative information in the network by blocking $K$ uninfected nodes, where $K$ is a given constant.

Definition 6 Blocking Set: Given a network structure $G$, the initial infected node set is $T \subseteq V$. The blocking set is defined as $S (S \subseteq \{V - T\} | |S| \leq K)$. The influence minimization problem can be expressed as the following optimization problem:

$$\text{Minimize}_{S \subseteq \{V - T\}} |T|/|V - S| (|S| \leq K)$$

(10)

Where $|T|/|V - S|$ represents the number of nodes that the initial infected node set $T$ eventually spreads in the network when the node set $S$ is blocked.

Solving the optimal problem (10) directly in a large network is an NP hard problem. Therefore, a heuristic algorithm is considered to solve the approximate optimal solution.
Paper tries to achieve the negative influence minimization goal by blocking certain nodes near the initial infected nodes.

**Definition 7 n-Neighbor Nodes Set:** Given a network structure \( G \), the initial infected node set is \( T (T \subseteq V) \). The \( n \)-Neighbor node set of node set \( T \) is defined as \( N(T) \), where \( SD(u, v) \) represents the shortest path between nodes \( u \) and \( v \).

\[
N(T) = \{ u \in V - T | \exists v \in T, s.t. SD(u, v) \leq n \}
\]

To further simplify the NP hard problem, a heuristic method of blocking \( K \) nodes from the \( N(T) \) set is used to identify the approximate optimal solution to achieve the goal of suppressing the spread of the negative influence.

In the IMCG algorithm, the value of \( n \) is used to delineate the range of node sets that need to be tested for each iteration. As the value of \( n \) increases, the optimal blocking node is found in a wider range of node sets. Increasing the value of \( n \) may achieve a better suppression effect; however, simultaneously, a sharp increase in the search range would consume a large amount of time. A natural idea is to block the nodes near the infected nodes. Therefore, in the synthetic network, based on the small world theory, the maximum value of \( n \) is set as 6, the range of \( n \) values are 1–6, and the suppression effect of the IMCG algorithm under different \( n \) value settings is observed. It can be seen from FIGURE 6 that the suppression effect of the IMCG algorithm exhibits a slight improvement with the increase in the \( n \) value; however, a good suppression effect can also be obtained when the \( n \) value is 1 or 2. Therefore, this aspect can avoid a sharp increase in the search range due to an increase in the value of \( n \).

**FIGURE 6.** The sensitivity of \( n \) value on the IMCG algorithm

**Definition 8 Seed Set:** Given a network structure \( G \), the initial infected node set is \( T (T \subseteq V) \). We define the seed set as \( \{ S_0, S_1, S_2 \ldots S_K \} \), where \( S_0 = \emptyset, S_1 = S_{i-1} \cup \{ u_i \in V - T | u_i \text{ is the node blocked in round } i \} \). \( u_i \) satisfies equation (12)

\[
u_i = \arg\min_{u_i \in V - T - S_{i-1}} \{ \sigma[T|V - S_{i-1} \cup \{ u_i \}] - \sigma[T|V - S_{i-1}] \}
\]

III. Design of influence minimization algorithm based on the coordinated game

Algorithm 1 presents the main steps of the IMCG algorithm. In the first stage of the IMCG algorithm, the value of the benefit space in the coordinated game model is quantified according to the local interaction models. In the second stage of the IMCG algorithm, the influence minimization model determines the nodes in the network that will be infected under the influence of its infected neighbor nodes based on the node strategic choice, which is defined in the coordination game model. Subsequently, the algorithm determines the seed nodes to be blocked to suppress the spread of the negative influence.

**Algorithm 1**

**IMCG Algorithm**

**INPUT:** \( G = (V, E, \lambda), T, n, \lambda, K \)

**OUTPUT:** Seed set \( S_K \)

1: \( \text{seed set } S_0 = \emptyset, \Delta = 0, \Delta_w = \emptyset \)
2: // The first stage of the IMCG algorithm
3: \( \text{execute Algorithm 2 to calculate the benefit space } i \text{ in the local interaction model} \)
4: // The second stage of the IMCG algorithm
5: \( \text{Calculate the } n \text{-neighbor node set } N(T) \text{ according to equation (11)} \)
6: \( \text{for } i = 1 \text{ to } K \text{ do} \)
7: \( \text{execute Algorithm 3, find the } i \text{-th seed node that conform the influence minimization model based on the coordinated game model} \)
8: \( S_i = S_{i-1} \cup \Delta_w \)
9: \( \text{end for} \)
10: \( \text{Output seed set: } S_K \)

In the first stage of the IMCG algorithm, first, the initialization operation is performed, and the node similarity is calculated according to equation (3). When the initialization operation ends, the algorithm enters the local interaction phase. According to the three local interaction modes described above, equations (4), (5), and (7) are respectively used to calculate \( DI, CI \), and \( EI \). Finally, the benefit space \( i_{uv} \) and \( i_{vu} \) are calculated according to equation (9). After acquiring the benefit space, the algorithm enters the stage of finding the seed set \( S_K \). The pseudocode is presented as Algorithm 2.

**Algorithm 2**

**LOCAL INTERACTION NODES**

**INPUT:** \( G = (V, E, \lambda) \)

**OUTPUT:** Benefits space \( i \)

1: // Initialize
2: \( \text{for } \forall e = \{u, v\} \in E \text{ do} \)
3: \( \text{execute the equation (3) to calculate the initial similarity } s(u, v) \text{ between the node } u \text{ and } v \)
4: \( \text{end for} \)
5: // Local interaction
6: \( \text{for } \forall e = \{u, v\} \in E \text{ do} \)
7: \( \text{execute the equation (4)-(5)-(7) separately, calculate } DI, CI, EI \)
8: \( S_i^{(u,v)} = s(u, v) + DI_i + CI_i + EI_i \)
9: \( \text{calculate the benefits space } i_{uv}, i_{vu} \text{ by the equation (9)} \)
10: \( \text{end for} \)
11: \( \text{Output seed set: } S_K \)
seed set. Finally, the seed set $S_K$ containing $K$ nodes is output. The pseudocode is shown in Algorithm 3.

**ALGORITHM 3**

**LOOKING FOR SEED SET: $S_K$**

**INPUT:** $G = (V, E, z)$, $T$

**OUTPUT:** SEED NODE $\Delta_n$

1: $\Delta = 0$, $\Delta_u = \emptyset$
2: for $u \in \{N(T) - T - S_{i-1}\}$ do
3: Block node $u$, calculate the number of nodes that are ultimately infected according to equation (1)
4: if $\sigma(T|V - S_{i-1} \cup \{u\}) - \sigma(T|V - S_{i-1}) < \Delta$
5: $\Delta_u = u$
6: end if
7: end for
8: Output seed set: $\Delta_u$

**IV. Experiment**

To prove the effectiveness of the proposed IMCG algorithm, experiments were carried out on four real networks, and the algorithm was compared with five other comparison algorithms. Under the linear threshold and weighted cascade model diffusion model, by infecting some initial nodes and blocking $K$ uninfected nodes, the number of nodes that were ultimately infected was used as an algorithm performance evaluation index.

**Data Set:** The four real data sets include two Facebook networks, Reed98[27] and Hamsterster[27], a football team alliance network, Football, and a consumer review trust network, Epinions[27]. The statistical information of the four data sets is summarized in Table 1.

<table>
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<th>TABLE 1 DATA SETS STATISTICS INFORMATION</th>
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<tr>
<td><strong>Data sets</strong></td>
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<td>Reed98</td>
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<tr>
<td>Hamsterster</td>
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<tr>
<td>Epinions</td>
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</tbody>
</table>

**Algorithm:** Six algorithms were tested in this work. In addition to the proposed IMCG algorithm, five other algorithms were used as the comparison algorithms.

1) **IRIE:** The IRIE algorithm integrates the influence ranking and influence estimation. The research of K Jung[28] shows the effectiveness of the IRIE algorithm in various networks and demonstrates its better stability compared with that of other algorithms[29].

2) **Betweenness:** The Betweenness algorithm selects the node with the highest betweenness centrality as the seed node[30].

3) **PageRank:** PageRank is a link analysis algorithm, which assigns weights to the nodes in the network structure, and the affected nodes are considered to have higher PageRank values. In this paper, we use $\alpha = 0.9$ as a random jump parameter.

4) **Degree:** The Degree algorithm selects the node with the largest out degree. The study by Kempe D et al.[31] indicates that the nodes with the height degree may be superior to other heuristic algorithms based on the centrality in influencing other nodes.

5) **Random:** The Random algorithm randomly selects nodes.

**Diffusion Model:** For the TopK node set obtained by the six test algorithms, the linear threshold (LT) and weighted cascade model (WC) diffusion model[19,20,28] is used to evaluate the effectiveness of the six test algorithms based on the number of finally infected nodes.

**A. Parameter setting and experimental environment**

There are two important parameters in the IMCG algorithm: $\lambda$ and $n$. All the experiments were run on a PC with a 2.5 GHz CPU, 62.6 GiB memory, and a CentOS7 operating system.

Among the three interaction modes driven by the local topology, the third type of exclusive neighbor nodes plays a crucial role in the change in the similarity. The magnitude of $\lambda$ determines the level of the positive or negative influence of $\rho(u, z)$ on the similarity $s(u, v)$. In this paper, $\lambda$ is set to a reasonable value of 0.6[26].

The value of $n$ determines the range of the neighbor node set when solving the optimal problem (10). A larger value of $n$ means that more nodes are included in the $N(T)$ set. As $n$ increases, the algorithm tests for more invalid nodes. It is found through experiments that the value of $n$ is insensitive to the evaluation index, and a solution approximating the optimal solution can be obtained with a small value. In this paper, the value of $n$ is set as 2.

The linear threshold model samples the value of the activation threshold of each node $u$ uniformly at random from $[0, 1]$. The weighted cascade model assigns a propagation probability of $P_{uv} = 1/\text{deg}(v)$ to each edge.

**B. Real Network Experiment**

The performance of the six test algorithms was evaluated by performing experiments on four public real networks, all of which are available on the public dataset website. During the experiment, the effectiveness of the proposed IMCG algorithm was verified by setting different numbers of the initial infected nodes and blocking different numbers of the TopK nodes. The experiments were carried out in the case of $k = \{0, 10, 20, 30, 40, 50\}$ by changing the number of blocked nodes in all the data sets. We unified the range of the number of the initial infected nodes as 10–40 (interval of 10) in the weighted cascade diffusion model[19]. This operation was performed because a small number of initial infected nodes can cause a wide range of diffusion effects in this model. Subsequently, we conducted experiments under different conditions of the initial infected nodes, namely, 10, 20 and 10, 20, 30, 40, based on the number of nodes in different data sets. In the linear threshold diffusion model, a large-scale diffusion of negative information cannot be achieved when a small number of initial nodes are infected. If negative information does not spread, it is worthless to discuss the suppression
effect under this condition. Therefore, we unified the range of
the number of initially infected nodes as 250–400 (interval of
50) in the linear threshold diffusion model\cite{21}. Similar to the
weighted cascade diffusion model, we conducted experiments
under different conditions of the initial infected nodes, namely,
250, 300 and 250, 300, 350, 400, based on the number of nodes
in different data sets (The only exception is the football dataset.
Because this dataset has only 115 nodes, we set the initial
number of infected nodes as 40, 50).

1) Football Network

The Football network contains 115 nodes and 613 edges.
FIGURE 7 shows the number of the final infected nodes in the
network under the linear threshold diffusion model. This result
is a consequence of the blocking of the TopK nodes obtained
by the six test algorithms under different experimental
conditions with the related numbers of initial infected nodes
as $|T| = 40, |T| = 50$. The six algorithms did not exhibit a
significant difference before $K = 20$ nodes were blocked.
When more nodes are further blocked, the proposed IMCG
algorithm is superior to the other five comparison algorithms
in both the experiments. FIGURE 8 shows the number of the
final infected nodes in the network under the weighted cascade
diffusion model. This result is a consequence of the
blocking of the TopK nodes obtained by the six test algorithms
under different experimental conditions with the related
numbers of initial infected nodes being $|T| = 10, |T| = 20$.
The proposed IMCG algorithm exhibits a better effect than the
five comparison algorithms with the increase in the $K$ value.
2) Reed98 Network
The Reed98 network contains 962 nodes and 18,812 edges. FIGURE 9 shows the number of the final infected nodes in the network under the linear threshold diffusion model. This result is a consequence of the blocking of the TopK nodes obtained by the six test algorithms under different experimental conditions with the related numbers of the initial infected nodes being \( |T| = 250 \), \( |T| = 300 \). When \( K = 10 \), the IMCG algorithm can achieve a better suppression than the comparison algorithms. As the \( K \) value increases, the suppression effect of the IMCG algorithm is consistently better than that of the five comparison algorithms. FIGURE 10 shows the number of the final infected nodes in the network under the weighted cascade model diffusion model. This result is a consequence of the blocking of the TopK nodes obtained by the six test algorithms under different experimental conditions with the related numbers of the initial infected nodes being \( |T| = 10 \), \( |T| = 20 \). The results show that the suppression effects of the Random, Degree, PageRank, IRIE and Betweenness algorithms are similar. Furthermore, the proposed IMCG algorithm can achieve a more effective suppression than that of the abovementioned five algorithms.

FIGURE 9. LT Model of the Reed98 Network

FIGURE 10. WC Model of the Reed98 Network
3) Hamsterster Network

The Hamsterster network contains 2,426 nodes and 16,530 edges. FIGURE 11 shows the number of the final infected nodes in the network under the linear threshold diffusion model. This result is a consequence of the blocking of the TopK nodes obtained by the six test algorithms under different experimental conditions with the related numbers of the initial infected nodes being $|T| = 250$, $|T| = 300$, $|T| = 350$, $|T| = 400$. The results show that the Degree and PageRank algorithms have similar suppression effects. The Random, IRIE and Betweenness algorithms fail to achieve a better suppression on this dataset and perform poorly. The proposed IMCG algorithm can achieve more effective suppression than the five algorithms mentioned above.

FIGURE 12 shows the number of the final infected nodes in the network under the weighted cascade model diffusion model. This result is a consequence of the blocking of the TopK nodes obtained by the six test algorithms under different experimental conditions with the related numbers of the initial infected nodes being $|T| = 10$, $|T| = 20$, $|T| = 30$, $|T| = 40$. The experimental results show that the IRIE performs poorly on the Hamsterster network dataset. The other three algorithms, namely, Degree, PageRank and Betweenness exhibit a similar performance; however, overall, the stability of the IMCG algorithm is better than that of the other five comparison algorithms, and it can achieve better suppression.

FIGURE 11. LT Model of the Hamsterster Network
4) Epinions Network
The Epinions network contains 26,588 nodes and 100,120 edges. FIGURE 13 shows the number of the final infected nodes in the network under the linear threshold diffusion model. This result is a consequence of the blocking of the TopK nodes obtained by the six test algorithms under different experimental conditions with the related numbers of the initial infected nodes being $|T| = 250$, $|T| = 300$, $|T| = 350$, $|T| = 400$. The experimental results show that the IMCG algorithm has a better suppression effect than that of the five comparison algorithms. The suppression effects of the five comparison algorithms under the linear threshold model are poor, and the suppression effect is considerably inferior compared to that of the IMCG algorithm. FIGURE 14 shows the number of the final infected nodes in the network under the weighted cascade model diffusion model. This result is a consequence of the blocking of the TopK nodes obtained by the six test algorithms under different experimental conditions with the related numbers of the initial infected nodes being $|T| = 10$, $|T| = 20$, $|T| = 30$, $|T| = 40$. The experimental results show that the IMCG algorithm has a better suppression effect than that of the five comparison algorithms. At the same time, in the Epinions network dataset, both the Random and IRIE algorithms fail to suppress the spread of the negative information. The other three comparison algorithms exhibit similar effects.
**FIGURE 13.** LT Model of the Epinions Network
5) Experimental analysis

The suppression effect of the six test algorithms was evaluated by conducting experiments in four real network data sets. It is noted that when using the linear threshold model in the Football network dataset and setting $|T| = 40$, even if $K$ is increased to 30, the suppression effect of the IMCG algorithm is slightly weaker than those of the IRIE and Betweenness algorithms. Until $K$ increases to 40 and 50, the suppression effect of the IMCG algorithm surpasses that of all the comparison algorithms. The main reason for this phenomenon is that the number of nodes included in the Football network dataset is small. When the number of the initial infected nodes is 40 and 50, the number of nodes that can be selected and blocked is not extremely large. Therefore, even the Random algorithm can choose a set of seed nodes that have a satisfactory suppression effect.

Using the weighted cascading model in the Football network dataset and experimenting on the remaining three datasets, we can see that the IMCG algorithm has a better suppression than that of the five comparison algorithms for $K$ values beyond $K = 10$. This phenomenon occurs because the number of nodes that are available for the selection and blocking is large, which avoids the situation shown in FIGURE 7. However, it should be stated that this aspect does not mean that a larger number of nodes available for selection and blocking corresponds to a better suppression effect of the IMCG algorithm. The relevant experiments are explained in Definition 7 and FIGURE 6.

From the experimental results shown in FIGURE 7 to FIGURE 14, the IMCG algorithm can be noted to achieve better experimental results than those of the comparison algorithm, and the effectiveness of the algorithm is proved by these experiments.
V. Conclusion
This paper proposes an influence minimization algorithm based on the coordinated game, which minimizes the propagation of the negative information by blocking the propagation ability of the $K$ seed nodes in the network. The proposed approach initially solves the problem of suppressing the spread of the negative information in the network when some nodes in the network are initially infected by the negative information. Compared with that of the five comparison algorithms, the proposed algorithm has a better experimental effect on the real network data sets.

At present, the proposed IMCG algorithm is still immature and lacks the capacity to be extended to large scale data sets because the time complexity of the algorithm is still excessively high. Therefore, in future work, one of the key research directions should be further reducing the time complexity of the algorithm and extending its application to a larger network structure.

Furthermore, to acquire a set of TopK nodes with better suppression effects, introducing user based internal attributes must be considered in future research. This aspect may involve including the number of friends and the interests of users, as well as some external attributes based on the social theory, for instance, the opinion leaders, structural holes, and social balance.

REFERENCES
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