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DEVELOPING GAME THEORY-BASED METHODS FOR MODELING INFORMATION CONFRONTATION IN SOCIAL NETWORKS

Abstract: This paper explores the essential dynamics of social networks, specifically examining the phenomenon of information confrontation among users. The goal of the research is the development of a novel simulation methodology that integrates game-theoretic principles with probabilistic techniques to provide a robust model for these interactions. The theoretical framework of the study is founded on the conceptualization of user conflicts as a strategic game between two players. The primary objective for each player in this game is to exert influence and control over as many nodes within the network as possible. To capture the essence of these strategic interactions, we have introduced an innovative algorithm that facilitates dynamic strategy adaptation. This algorithm is pivotal in allowing players to modify their decision-making processes in real-time, based on the continually changing conditions of the network. For practical implementation and validation of the methodology, we used the Facebook Researcher open dataset, with a particular focus on its Kazakhstani segment. This dataset provides a rich source of empirical data, reflecting diverse user interactions and network configurations, which are essential for testing the model. This approach stands out by offering significant improvements in computational efficiency and resource management. By dynamically tracking and updating the network's status, the proposed method reduces the computational resources required, thereby enhancing the scalability of the simulation. In comparing our methodology with other existing models in the field, it becomes evident that it not only matches but in several respects surpasses these methodologies in terms of flexibility. This study makes substantial contributions to the field of social network analysis by providing a sophisticated tool that can be effectively employed to navigate and analyze the complexities of information confrontation in digital social spaces.

Keywords: game theory; strategy adaptation; social networks; information conflict; simulation algorithm; probabilistic approach; analytical systems.

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Introduction (Literary review)

This study investigates the imperative role of social networks in information dissemination, communication, and entertainment, emphasizing their centrality in contemporary digital society. The escalating complexity and widespread utilization of social networks underscore the need for more sophisticated analytical techniques. Data reveal that individuals spend an average of 144 minutes per day on social media, a trend that has increased consistently over the past decade, highlighting social networks' role in fostering information conflicts, including efforts at manipulation and misinformation dissemination.

Research into the modeling of information influence and management on social networks dates back to the late 1990s [1]. The relative lack of regulatory oversight, coupled with the anonymity provided by the internet, creates opportunities for malicious actors to propagate harmful content. This study delves into the arena of information warfare, which encompasses diverse scenarios wherein information is strategically utilized to achieve specific objectives, often pitting various parties against each other in contexts such as corporate rivalries, political disputes, propaganda efforts, and anti-misinformation campaigns.

Given these dynamics, it is crucial to analyze the structure of social networks to bolster online security, prevent the spread of harmful content, and tackle issues such as botnets. The increasing complexity and dynamism of social networks necessitate the development of new, more effective analytical methodologies [2]. This paper advocates for innovative approaches to enhance the accuracy and efficiency of social network analysis in light of these evolving challenges.

This research introduces an innovative approach to social network analysis within the framework of information conflicts. It integrates game-theoretical principles with probabilistic models of information dissemination and dynamic network modeling. Additionally, it presents a sophisticated algorithm for real-time monitoring and strategy adjustment among network entities. The objective is to establish a model for information confrontation between two entities, designated as A and B, that surpasses existing methodologies in terms of efficiency and resource utilization. The validity and applicability of the proposed model are affirmed through extensive testing on large-scale network models, highlighting its relevance and practical utility in contemporary social network analysis.

The field of social network analysis includes a large number of research interests and methodologies, reflecting its significance in understanding complex social structures and behaviors. Studies in this domain have traditionally focused on varied aspects such as information warfare, community detection, node influence and centrality, viral information dissemination, recommendation systems, and sentiment analysis within networks. Various analytical techniques such as graph theory, machine learning, clustering, genetic algorithms, natural language processing, and game theory have been employed to dissect these phenomena [3].

Our research situates itself within the context of information confrontation in social networks, a key aspect of information warfare. The process of information dissemination forms a crucial component of this confrontation. Traditionally, models for information dissemination in social networks are categorized into graph-based and non-graph-based approaches. Among the graph-based models, the Independent Cascades (IC) model [4] and the Linear Threshold (LT) model [5] are particularly prominent. The Linear Threshold model operates under the premise that a node becomes activated when the influence from its activated neighbors surpasses a predefined threshold. This model aptly simulates situations where community or group decisions are critical, effectively mirroring real-life scenarios like the adoption of new products or ideas once they gain sufficient traction within a community. This model also sheds light on social influences impacting decision-making, often cited in studies of phenomena such as the "tipping point effect." However, the LT model's primary limitation is its focus on collective thresholds rather than individual decision-making processes, which are vital in networks where personal decisions are pivotal. Additionally, it assumes static thresholds for each node, disregarding the potential dynamics and fluctuating conditions affecting individual nodes over time.

Conversely, the Independent Cascade model describes a scenario where each activated node has a single opportunity to activate each of its inactivated neighbors with a specific probability. This model is particularly suited to scenarios that mimic the viral spread of information, where one node's activation can lead to a chain reaction across the network. Nevertheless, the IC model's simplicity – each node having only one chance to activate its neighbors—may not fully capture the repeated efforts users often make in real interactions, nor does it accommodate the long-term dynamics of node interactions within continually evolving networks.

While both models operate on a discrete time axis where the information dissemination process is iterative and synchronous, starting from initially activated nodes [6], there have been adaptations to enhance their applicability and efficiency. For instance, some studies have introduced variations of the LT model that incorporate factors like content virality and user-specific probabilities of information acceptance [7]. Additionally, asynchronous versions of these models have been developed to optimize resource usage and improve computational efficiency, addressing some of the synchronous models' limitations [8].

In addition to graph-based approaches, models that do not rely explicitly on predefined network structures, such as the Susceptible-Infectious-Recovered (SIR) and Susceptible-Infectious-Susceptible (SIS) models, are instrumental in understanding network dynamics [9]. These epidemiological models assess the state of each node and track changes in population segments over time using differential equations. They operate under the assumption of random interactions among nodes, which simplifies the analysis but might not capture the unique structural properties of specific social networks, thus limiting their detailed applicability to social phenomena.

Further enriching the toolkit for social network analysis, probabilistic models, influence maximization algorithms like Cost-Effective Lazy Forward (CELF) and CELF++ [10], network monitoring optimization algorithms, and game-theoretic frameworks for modeling information influence [11] have also been developed. Game-theoretic approaches, in particular, have gained prominence. For example, one study [12] employs game theory to devise strategies for blocking influence maximization using oracles to generate mixed strategies for the players, while another [13] builds on this with a hierarchical algorithm to enhance the method's efficiency. However, these methods face challenges when applied to large-scale real-world networks due to their computational intensity and time requirements. For instance, identifying optimal nodes for monitoring a Twitter subnetwork with 11,000 nodes and 25,000 connections required approximately 28.7 hours in one study, highlighting the significant resource demands of these analyses.

The limitations of existing approaches often revolve around the assumption of static network conditions—despite the inherently dynamic nature of real networks—or the substantial computational resources required for processing complex network structures. The ongoing escalation in network complexity further complicates the analysis of modern networks using traditional methodologies. To address these challenges, we introduce a novel game-theoretic model combined with Markov probabilistic models for information dissemination. This hybrid model incorporates a streamlined one-oracle approach to reduce computational demands while capturing the dynamic interactions and strategic behaviors of entities within the network. The specifics of this model and its application are explored in subsequent sections of this study, where we detail its design, implementation, and the insights it offers into effective information warfare strategies between players A and B.

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Methods and Materials

Any social network can be depicted as a graph G = (V, E), where V represents the vertices, corresponding to user accounts, and E denotes the edges, signifying the connections between these accounts. These graphs may be either directed or undirected. In a directed graph, connections have a specific orientation, meaning that if user A follows user B, it does not necessarily imply that user B follows user A. Twitter is a typical example of a directed graph, while networks like Facebook are examples of undirected graphs.

The process of information dissemination on social media can cause certain pieces of information to gain fame and even become viral, spreading rapidly across the globe. This process generally unfolds in two primary stages:

Initial Distribution: Information is shared within a user's immediate circle through personal messages or public posts;

Further Distribution: The information then propagates along the network's edges according to the specific rules of the graph that models the network.

Each user within a social network exercises their judgment to either trust or dismiss the information they encounter. Furthermore, the decision of each user is influenced by the opinions and actions of others within the same network, a phenomenon known as social influence. One straightforward method to model the dissemination of information is to consider each node in the graph as activated if the node receives and accepts the information, and not activated if the node either does not receive or does not accept it.

Fig. 1 illustrates a directed graph connecting five users. In this diagram, the weights on each edge indicate the strength of the connection between users. A higher weight suggests a greater level of trust between the users, which is crucial in the context of information dissemination, as users with stronger or more influential connections are more likely to trust each other.

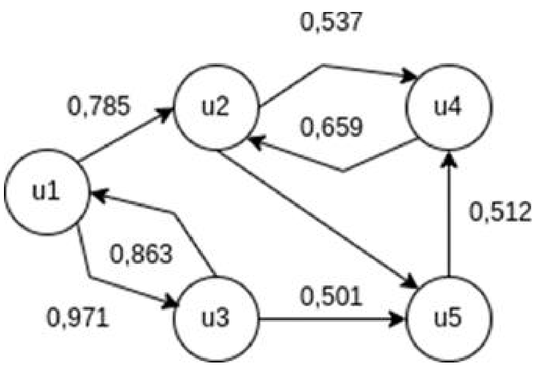

Figure 1. A directed graph with 5 users and connections between them

This modeling approach is visualized in Fig. 2, where nodes that have accepted the information are highlighted in red. Then we adopt this modeling strategy in our research.

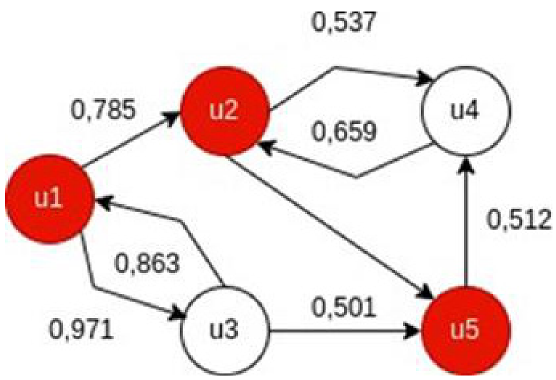

Figure 2. The process of node activation during the information diffusion

The Information Influence Model is designed to explore the impact of information on user behavior. Its primary objective is to determine how the information environment and the user's awareness of information shape their decision-making processes. By employing this model, researchers can analyze how information flows within a network affect user behavior and decision-making. Because social networks can be used as the arena for various types of information confrontation, when analyzing social networks in the context of this confrontation, traditionally, three main nested classes are analyzed: Information Influence, Information Management, and Information Confrontation, as shown in Fig. 3.

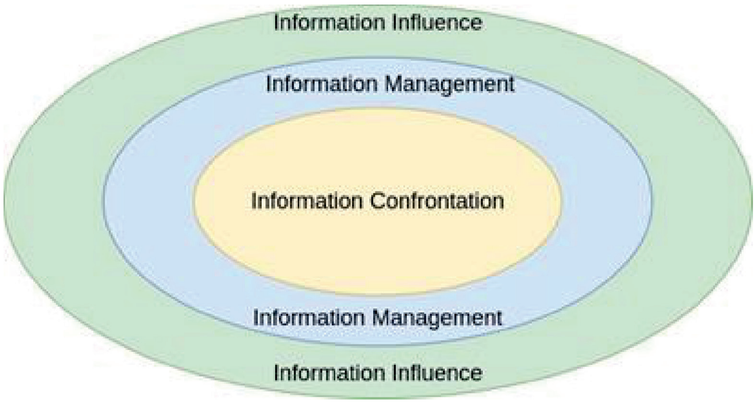

Figure 3. A model of information influence, management and confrontation

Expanding upon the Information Influence Model, the Information Management Model introduces an additional layer of complexity by incorporating deliberate control over user behavior through targeted information influence. This extension allows for a more nuanced understanding of how information can be strategically managed to guide or alter user behaviors within the network. This approach is crucial for studies aimed at understanding the dynamics of information control and its implications on individual and collective actions within social networks.

The primary objective of this model is to devise approaches that controls the user in a specific direction. Consider two influencers, A and B, each capable of molding the initial strategies of selected players within a social network. Suppose $A, B \subseteq N$ represents individuals influenced by A and B, ensuring that $A \cap B = \emptyset$.

If we presume that information control is such consistent context [14], it follows that all in these group adopt viewpoints of $u \in U, v \in V$ in such contexts being subsets of R. The shift in an agent's stance within the social network, considering their own viewpoint and those of adjacent peers, can be formulated as expression:

$$x^t_i = \sum a_{ij} * x_j^{t-1},\ t = 1,2,\ \dots,\ i \in N. \tag{1}$$

According to [15] this expression (1) can be simplified as $X = \sum r_j * x_j^0$ and in the context of information management can be expanded to $X(u,v) = r_A u + r_B v + X^0$, meaning that the final opinion of the social network agents is linearly dependent on management factors u and v with the weights $r_A > 0$ and $r_B > 0$, where $r_A + r_B <= 1$.

Finally, using the model of information management makes it possible to model the information confrontation between users having opposing interests and wanting to influence the subjects of the network. To form a game-theoretic model of player interaction, it is necessary to determine the objective function of each player. For instance, the objective function of a certain player can be determined as follows [15]:

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$$f(u,v) = Q_A(X(u,v)) - C_A(u), \quad (2)$$

where $Q_A(X(u,v))$ is the quality function of changing the opinion of a particular agent by player A; $CA(u)$ is the cost function, i.e. the resources spent by player *A* to change the opinion of a certain agent.

According to [15], the assortment of objective functions $G = \{fA(u,v), fB(u,v), u \in U, v \in V\}$ alongside the potential actions available constitute a multiple series of games undifferentiated by the players' knowledge and sequence of play. When the game's mechanism for altering an agent's viewpoint are non-uniform across all players, who decide one, concurrently, and independently, the scenario is termed a game in biased form. This framework enables the identification of Nash Equilibria, where each participant, aware of others' strategies, cannot benefit by solely altering each other's strategy. The evaluation of player strategies' efficiency can be approached through Pareto criteria in such general contexts. This game within the realm of game theory for a non-cooperative game, is defined where every player's strategy is suboptimal, considering the other players' strategies, and any player stands to gain by independently changing their strategy. This concept is encapsulated mathematically as follows:

$$U_i(s_i^*, s_{-i}^*) >= U(s_i, s_{-i}^*), \quad (3)$$

where U_i is the payoff function for player i; s_i^* is the strategy chosen by player i in the Nash equilibrium; s_{-i}^* is the strategies chosen by all other players in the Nash equilibrium.

According to [16], two primary principles govern social influence within a social network: herd behavior and information cascades. An information cascade occurs when users disregard their own opinions and adopt the views or behaviors of others, based on the assumption that these others have acted on valid information – even if such information may not actually be sound. This process leads individuals to follow a chain reaction of decisions made by predecessors without critically evaluating the underlying information.

On the other hand, herd behavior involves individuals mimicking the decisions and actions of others but with the flexibility to modify these actions based on their personal perspectives [17]. In this scenario, while individuals are influenced by the group, they do not completely abandon their own judgments or insights. In our research, we have developed a model that incorporates these concepts of social influence. This model is visually represented in Fig. 4. Let us now delve deeper into each component of the depicted scheme to understand how these dynamics of social influence are integrated and modeled.

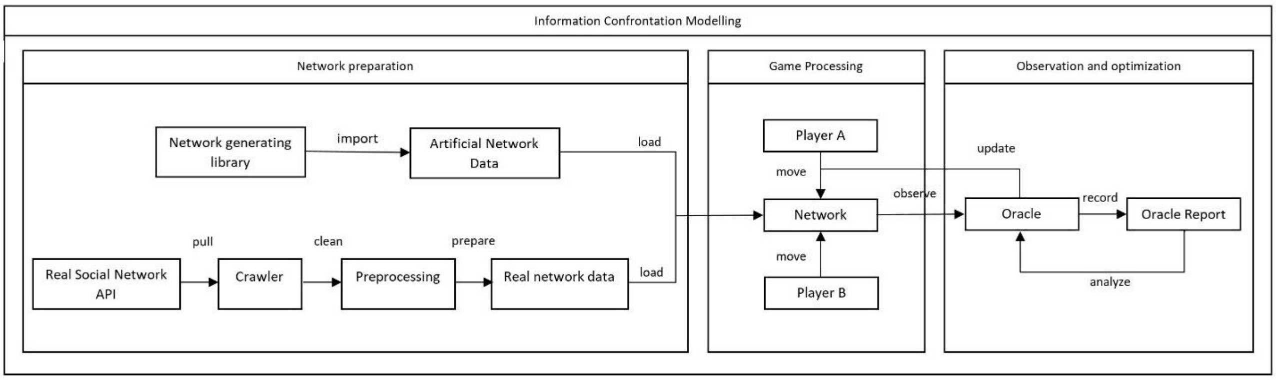

Figure 4. Information Confrontation Model

First of all, we designed an artificial network (See Fig. 5) using the Networkx [18], a Python library, to model different experiments and compare the results. We apply standard graph theory methods to model the social network. We have graph $G = (V, E)$ where vertices (V) are social network accounts and edges (E) are connections between them. Each vertex in the graph has a list of parameters required to process the model. As it is an information confrontation model, each node of the graph has the following parameters:

- *`A_trust_prob`, i.e. 0.1 <= `A_trust_prob` <= 1*: shows the probability that a user will be activated by player *A*;
- *`A_trusted`, i.e. `A_trusted`* ∈ *{1, 0}*: shows whether or not a user has been activated by player *A*;
- *`B_trust_prob`, i.e. 0.1 <= `B_trust_prob` <= 1:* shows the probability that a user will be activated by player B;
- *`B_trusted`*, *i.e. `B_trusted`* ∈ *{1, 0}*: shows whether or not a user has been activated by player *B*;
- *`spread_factor`, i.e. 0 <= `spread_factor` <= 1*: shows the ability of the user to spread gained information further to its neighbors;
- *`activity_rate`, i.e. 0 <= `activity_rate` <= 1*: shows how active the user is in the network.

To show the strength of connections between users, we integrated the weight factor upon each edge, showing the trust level *(`trust_level`, i.e. 0 <= `trust_level` <= 1)* between the users. With the help of this simulated network, we have conducted plenty of experiments, which will be discussed in detail in the "Experiments and Results" section.

However, having just an artificial network is not enough to make solid conclusions, so we decided to test our algorithm on real social networks. For that purpose, we decided to program the crawler system, which will be integrated with real social network APIs and pull publicly available data required for information confrontation modeling [19]. Then, the data will be cleaned and preprocessed, and after that, based on this data, the network model will be created and injected into the confrontation game. To keep the network dynamic, the Crawler will periodically pull new data from the actual network and inject it into our game. The part of the research that includes real-world network integration is currently in progress. That is why all the experiments presented in this paper are performed on the simulated artificial network.

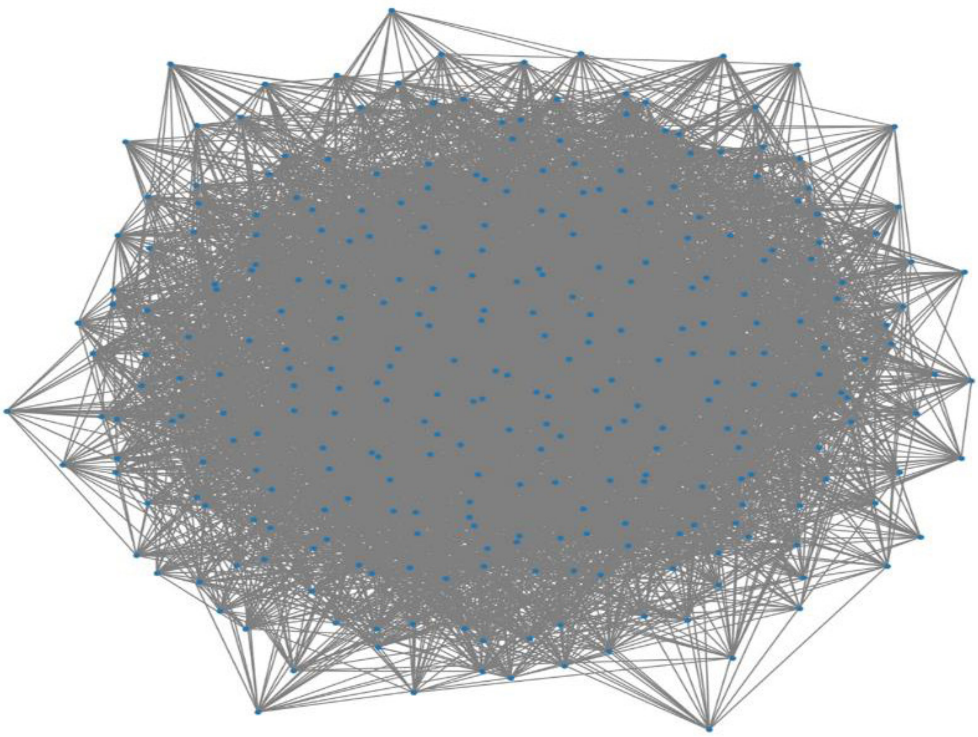

Figure 5. Artificial network model with 300 nodes

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We modeled information confrontation as the game of two players, A and B, that fight for influence in a particular social network. It can be two companies that want to gain the trust and loyalty of users. Each player aims to spread its information across as many users in social networks as possible, having limited resources. To reach this goal effectively, a player should adapt his strategy to respond to the changing environment, considering the current network state and the predicted opponent's strategy. A player has three options to move:

- It can send information to a particular user (i.e., try to activate it)
- It can try to switch the user activated by its opponent, thus luring the user to its side
- It can try to increase the likelihood that a particular user will believe his information

If the node is activated by player A it is colored red and if it is taken by player B it is colored blue. All other nodes are represented as gray. Fig. 6 shows how the information diffusion is generated by two players in our network model. The game lasts for a number of rounds settled at the initialization phase. At each round of the game, players choose the best move according to the cost function, i.e., the move that brings the highest profit to the user is selected. In our game, this cost function is as follows:

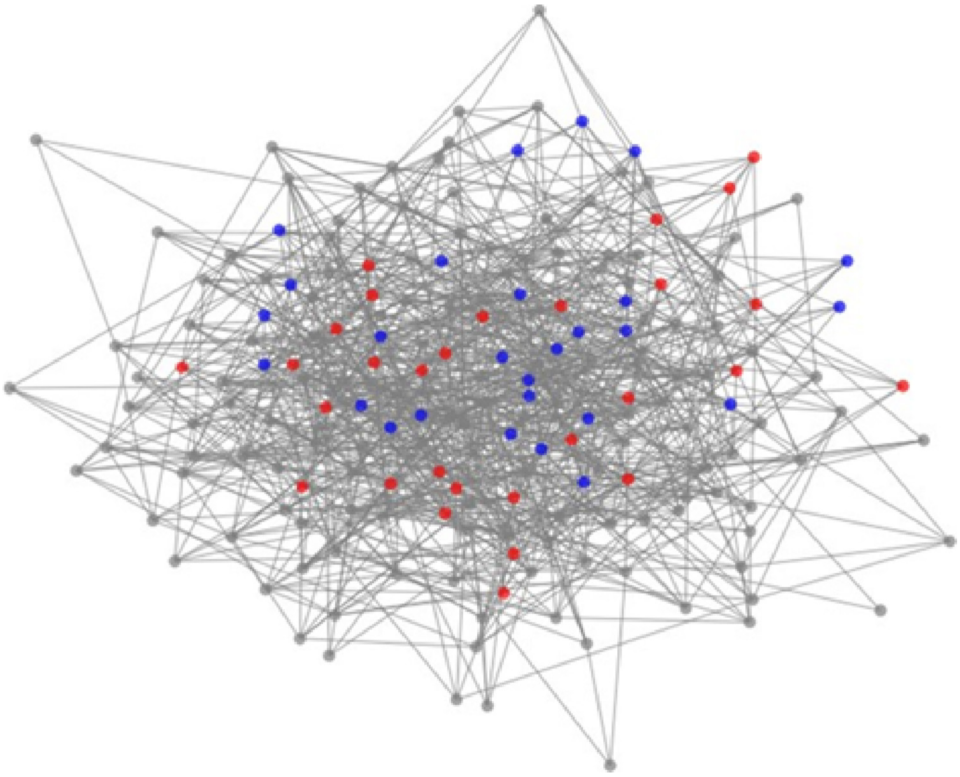

Figure 6. Information diffusion process by two players in the small network

$$Q = P(act)_{curr} * S_{fact_{curr}} * A_{rate_{curr}} + \sum i \in Neig\left(trust_{level(curr,i)} * P(act)_i * S_{fact_i} * A_{rate_i}\right), \qquad (4)$$

where $P(act)_{curr}$ – the probability that the current node will be activated by the given player; S_fact_{curr} – the ability of the current node to spread information further; A_rate_{curr} – the activity level of the current node in the network; *trust_level(curr, i)* – trust level between current node and its neighbor I; $P(act)_i$ – the probability that the neighbor *i* of the current node will be activated by the given player; S_fact_i – the ability of the neighbor to spread information.

This quality function considers not only the current node's parameters but also its neighbors' parameters to identify the nodes, the activation of which will maximize the spread of the information of the given player. This function also considers the willingness of the user to spread information further at a given time. For instance, the user may have a high spread factor, but at a given time, it may not want to spread information for some reasons such as bad mood, fatigue, frustration, etc. It is accomplished by including the randomness factor in the model to make nodes act like real-world social network users. Real-world social network users depend on plenty of random factors[20] such as mood, fatigue level, engagement in social network activity, etc. Therefore, it is essential to consider such factors when modeling the information dissemination process.

To optimize the model's performance, we designed an Oracle that constantly monitors the network and its state. This oracle tracks all the changes in the network at a given time and documents them in the report. With the help of this oracle, we can visualize the network and the state of each element at any given time during the model's execution. This oracle also keeps track of the inertial network changes provoked by a specific node's activation. These so-called "inertia changes" occur when an activated node tries to activate its neighbors without the engagement of any player. Using such an oracle significantly increases the speed of computations and minimizes the amount of resources consumed by the game.

Experiments and results

In this research, we proposed a novel approach for modeling information warfare between users in social networks based on game theory methods, probabilistic approaches for describing the spread of information, and dynamic algorithms for monitoring and tracking the state of the network at a given time. To find out how well the model does its job, we conducted several experiments on our artificial network, and we plan to conduct experiments on a real-world network in the future. First of all, we ran the model and analyzed how well two players adapted their strategies during the game. Several experiments conducted on networks with different numbers of nodes confirmed that users were able to effectively change their strategies according to the changing environment to gain maximum profit from each step. For instance, the results of a confrontation game with 100 rounds between two players A and B having limited resources in the network with 500 nodes, are shown in Figure 7. As it can be seen from Fig. 7, each player fights for influence in the network with dignity and uses resources efficiently.

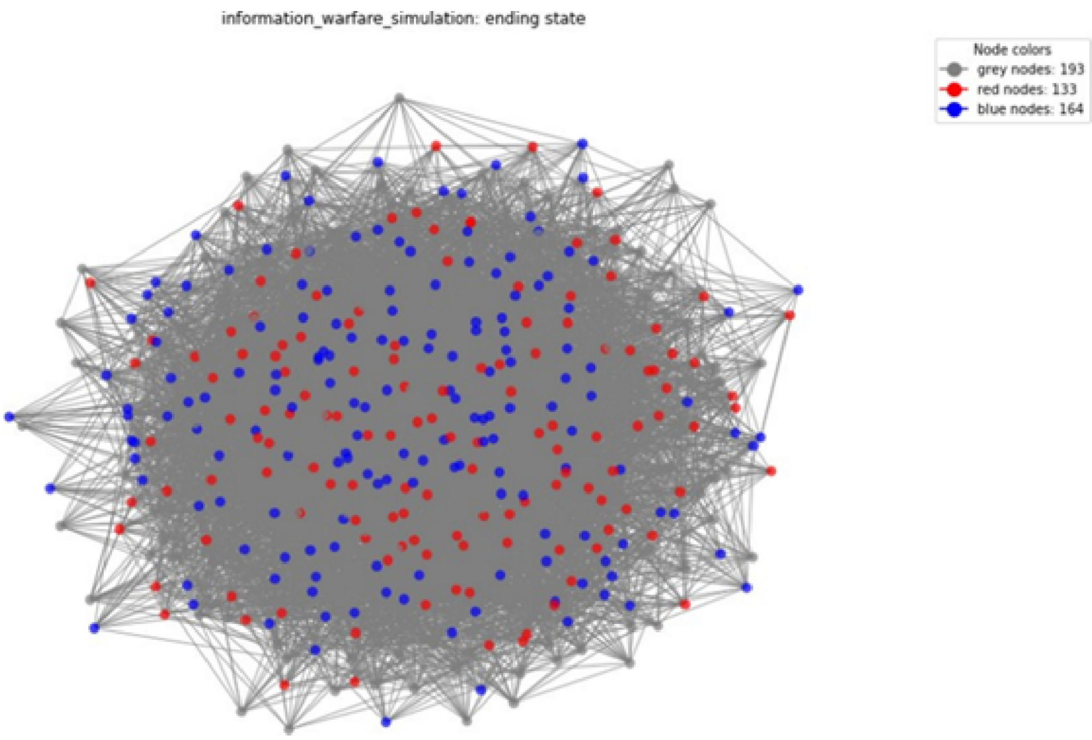

Figure 7. Confrontation between two players in the network with 500 nodes

Furthermore, we conducted comparison tests with other existing methods. The results of the experiments were compared with those of existing IC and LT models[21]. We evaluated the efficiency of each approach based on its ability to maximize the spread of the information in the network, taking into account the initial limitations of resources. We compared the elapsed time of each approach and RAM and CPU usage on the networks with the different number of nodes. The performance comparison is represented in Fig. 8.

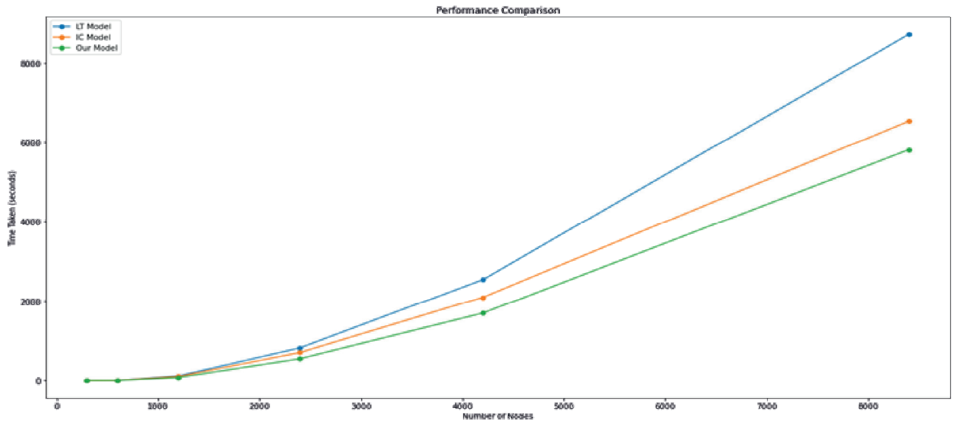

Figure 8. Performance comparison of a novel approach with other approaches

As can be seen from the graph, when the number of nodes was significantly small, all three models showed approximately similar results. However, when the number of nodes exceeded 1000, our model showed slightly better results than the others. Moreover, the execution time gap between these models became more prominent as the number of nodes in the network increased. Thus, at the end of the experiment, when the number of nodes was approximately 10,000, our model could process them in 5814 seconds, whereas 6541 seconds and 8722 seconds were required for processing by IC and LT models, respectively. In terms of CPU and RAM, our model has also shown promising results. As represented on Fig. 9 the IC Model consumed the highest amount of memory among those models, and our model consumed the least memory compared to the other models.

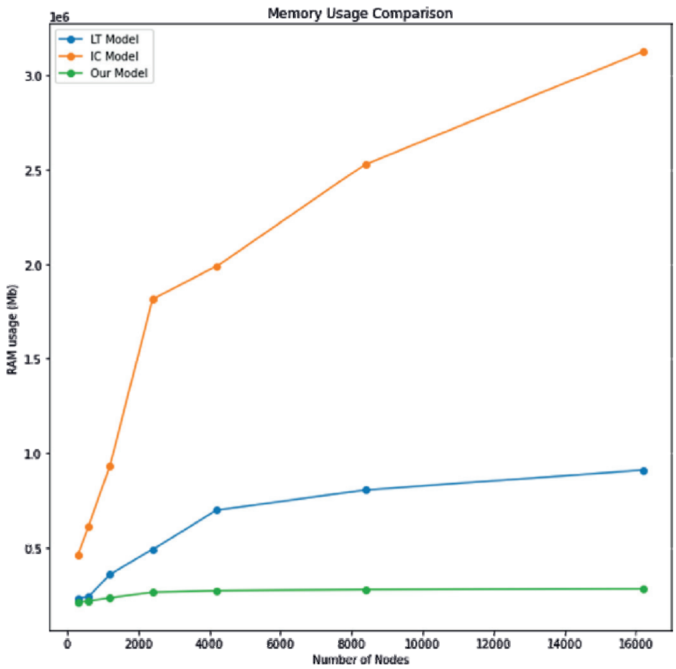

Figure 9. Memory usage comparison with other models

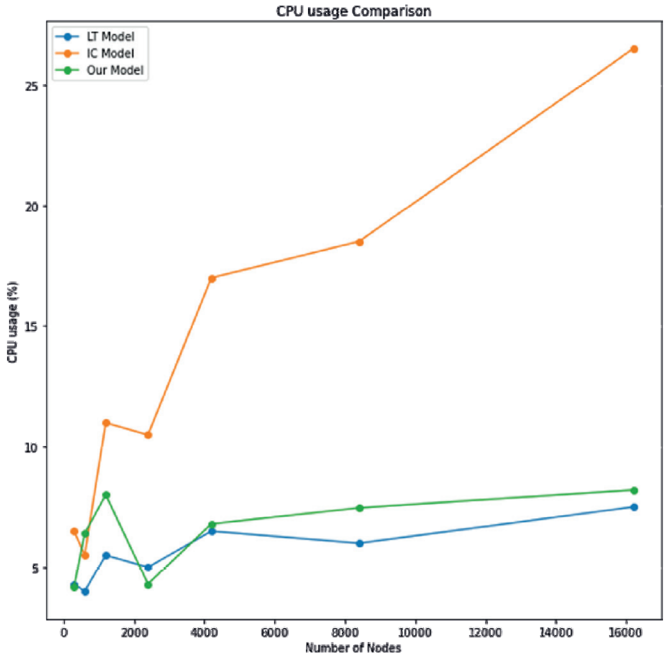

Figure 10. CPU usage comparison with other models

This model demonstrates superior performance in CPU consumption compared to the IC model, although it does not outperform the LT model, as shown in Fig. 10. However, the difference in CPU usage between the LT model and our model is minimal and not significant. Overall, our model has delivered satisfactory outcomes across numerous tests conducted on an artificial network with varying numbers of nodes. As we progress to the second phase of this research, which involves integration with a real-world network, we plan to further evaluate and compare the performance and resource utilization of these models in an actual social network setting. This comparison will provide deeper insights into the efficiency and practicality of our model when applied to real-world data, potentially confirming its viability for broader use.

Table 1. Performance metric across five different test cases for each model

Model	Performance				
	Test 1	Test 2	Test 3	Test 4	Test 5
LT Model	85%	87%	89%	91%	92%
IC Model	80%	83%	85%	88%	90%
Our Model	86%	88%	90%	92%	94%

Conclusion

The research began with the ambitious goal of modeling information confrontation in social networks using a new approach based on game theory. The pervasive nature of social networks and the multifaceted ways in which reliable and controversial information is disseminated on them emphasize the relevance of this study. Comparative analysis of our approach with existing models, such as LT and IC models, revealed meaningful findings.

While our model demonstrated competitive RAM and CPU utilization, especially on large networks, nuanced differences in computational efficiency highlight the potential of our approach. The LT model has shown a consistent and predictable level of CPU consumption, indicating its linear thresholding mechanism. In contrast, the IC model's CPU usage has exhibited

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a more volatile pattern, reflecting the stochastic nature of the cascading process. The obtained results suggest that the game theory approach maps well to the computational requirements of existing models [22] and offers a robust framework for capturing the complex dynamics of information propagation. In particular, the zigzag pattern of CPU usage in the IC model highlights the complex and unpredictable nature of the information cascade, which our game theory model handles more consistently and efficiently.

Conducted experiments allowed us to identify gaps in existing models, such as limited adaptability to dynamic changes in user behavior and network structure. This approach provides deep insight into the interaction mechanisms in the information space, considering many factors, including probabilistic estimates and game theoretical strategies. The most notable novelty of our work is integrating game theory with dynamic probabilistic and monitoring algorithms, which allows real-time adaptation of information dissemination strategies. It represents a significant advance in information warfare research, offering a more granular and adaptive approach to managing information flows [23].

Furthermore, in future research, we plan to integrate an automatic crawler mechanism into our model that will be used to extract data through social network APIs [24], thereby ensuring that the input data for the modeling is up to date. This modification involves a significant deepening of the methodological approach by providing access to actual information flows and structures of social interactions. The resulting graph of a real social network will serve as the foundation for analytical work, allowing the model to operate with data reflecting the current state of social media. This approach significantly increases the validity of the model since it becomes capable of verification based on current data, thereby ensuring a high level of reliability of research results.

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