Research on Weibo Rumor Propagation Mechanism Based on Big Data

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Abstract. Weibo's wide reach and openness make it a platform for both influence and the spread of rumors, causing negative social impacts. Therefore, studying the dissemination of rumors on Weibo holds important practical significance. This research takes the recent "Starch Sausage Incident" as a case study, expanding the traditional SIR model by incorporating a rational population, resulting in the SIRW model. Utilizing web scraping techniques to collect Weibo data, the study conducted data preprocessing and performed sentiment analysis using a GRU model. By combining sentiment results with user profile information, the research analyzed the cumulative numbers in various compartments over different time periods. Parameters were fitted using the least squares method, and the results indicate that the model performs well. Considering the characteristics of Weibo, the study employed a BA scale-free complex network for visual simulation and analyzed the impact of the degree and number of initial infected nodes on rumor propagation. Through robustness analysis, the research explored effective strategies for interrupting rumor transmission from the perspectives of large nodes and bridge nodes, proposing targeted public opinion control recommendations. The study demonstrates that a higher initial proportion of rational individuals significantly restricts rumor spread; conversely, a moderate number of rumors may enhance individuals' rationality and discernment. During different stages of rumor propagation, targeting hub nodes or bridge nodes can markedly improve the effectiveness of disruption.

Keywords: Rumor Propagation, Web scraping Technology, Text Sentiment Analysis, SIR Model, BA Scale-free Complex Networks.

1. Introduction

With the development of artificial intelligence and big data, the rapid expansion of the internet has brought about the risk of rumor propagation, resulting in negative impacts on society. Therefore, it is particularly important to identify rumors and establish mechanisms for their interruption. Stefanos Ougiaroglou and his team conducted a multi-level classification study on sentiment and citation intent in academic texts, effectively addressing the complexity of academic language by combining dictionary methods and machine learning, making it suitable for multilingual scientific communication [1]. Adepu Rajesh and Trambak Hiwarkar employed a multi-channel CNN with BiLSTM and attention mechanisms for sentiment analysis, demonstrating an accuracy of 94.13% on the IMDB dataset [2]. Guixian Xu and his team utilized an extended sentiment dictionary and a naive Bayes classifier, significantly improving sentiment classification accuracy across multiple domains [3]. Wei Xu and his team achieved an accuracy of 94.8% on the test set using a bidirectional GRU model [4]. M. K. Shamshudeen and his team analyzed the applications of AI and big data on the internet [5]. Amir H. Gandomi and his team applied machine learning and natural language processing to enhance data processing efficiency and user experience [6]. Yiou Lin and his team studied the mechanisms of online rumor propagation in China during the COVID-19 pandemic, finding that rumors spread rapidly before gradually declining [7]. Jianhong Chen and his team investigated the hesitation mechanisms involved in rumor propagation [8]. Rafal Rak expanded the Barabási-Albert model to generate new scale-free networks [9]. T.C. and his team explored how to leverage key nodes to influence public opinion, concluding that increasing the exposure rate of positive content among high-impact groups helps alleviate public sentiment issues [10].

Dictionary-based text sentiment analysis has limitations concerning internet slang, and the traditional SIR model for rumor propagation does not adapt well to complex networks. Therefore, this paper proposes a new SIRW rumor propagation model that combines GRU-based sentiment analysis with the least squares method, suitable for BA scale-free networks, to construct a model capable of simulating rumor propagation and achieving timely interventions.

2. Methods

2.1. Web Scraping Technology

Web crawlers, also known as web spiders, are programs that automatically retrieve resources from the internet. General crawlers capture all HTML pages from a given URL to create content mirrors but are unable to handle dynamically loaded content, such as that generated by Ajax and JavaScript rendering. Focused crawlers, on the other hand, are customized based on user requirements to filter and retain the desired information. This paper employs the Scrapy framework for crawling, which consists of several components: the Scrapy Engine, Scheduler, Downloader, Middleware, Spider, Items, and Item Pipeline.

2.2. GRU Model

The Gated Recurrent Unit (GRU) [11], introduced by Kyunghyun Cho et al. in 2014, is a variant of recurrent neural networks (RNNs) designed to address the vanishing and exploding gradient problems encountered in long sequences. GRUs are commonly used in natural language processing tasks like machine translation, text generation, and sentiment analysis due to their effectiveness with sequential data. The model introduces update and reset gates: the update gate controls memory retention, while the reset gate adjusts the influence of the current state on the output. The GRU architecture consists of an input layer, hidden state calculations, and an output layer. The overall structure is illustrated in Figure 1.

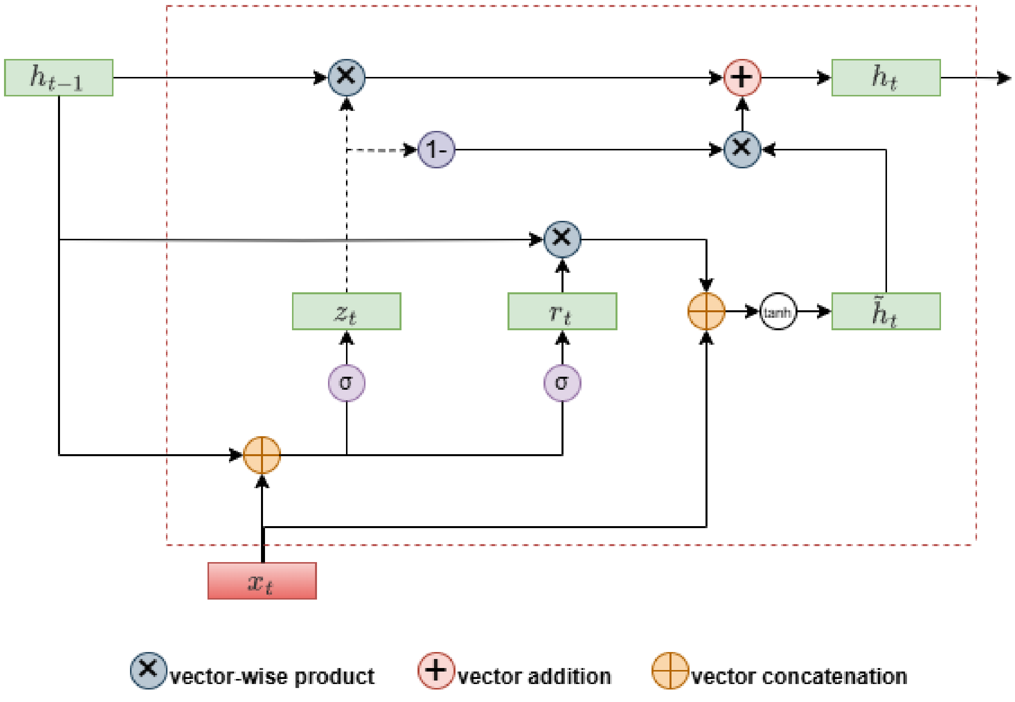

Figure 1. Architecture of the GRU Model

The update gate, reset gate, and candidate state are calculated as follows:

Update gate: Determines the influence of previous hidden states and current inputs:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{1}$$

Where z_t is the update gate, W_z is the weight matrix, σ is the activation function, $[h_{t-1}, x_t]$ represents the concatenation of the previous hidden state and the current input.

Reset gate: Controls the previous hidden state's influence on the candidate state:

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{2}$$

Where r_t is the output of the reset gate and W_r is the weight matrix for the reset gate.

Candidate state: Combines the current input and previous hidden state:

$$\tilde{h}_t = \tanh(W_h \cdot [r_t \odot h_{t-1}, x_t]) \tag{3}$$

Where $\tilde{h}_t$ is the candidate hidden state and W_h is the weight matrix for the candidate state.

The final hidden state is a weighted combination of the previous hidden state and the candidate state:

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{4}$$

2.3. Least Squares Method

There is a set of observed data points$(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$, along with a hypothetical model $y = f(x, \theta)$, where $\theta = (\theta_1, \theta_2, \ldots, \theta_m)$ represents the parameters to be determined. The error between the observed values and the model predictions is defined as $e_i = y_i - f(x_i, \theta)$. The objective of the least squares method is to choose appropriate parameters θ, to minimize the sum of the squares of all errors, defined as follows:

$$S(\theta) = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} (y_i - f(x_i, \theta))^2 \tag{5}$$

Where $S(\theta)$ is the residual sum of squares function. The task of the least squares method is to optimize $S(\theta)$ to find the parameters θ that minimize it.

In practical applications, models often exhibit non-linear relationships, in which case the least squares method can be extended to non-linear models. For a general non-linear model $y = f(x, \theta)$, the optimal parameters cannot be obtained directly through an analytical solution, so iterative optimization algorithms, such as gradient descent or Newton's method, are required. The basic steps are as follows: first, initialize the parameters $\theta^{(0)}$, then compute the gradient of the residual sum of squares function $S(\theta)$ and iterate according to the following update formula:

$$\theta^{(k+1)} = \theta^{(k)} - \alpha \nabla S(\theta^{(k)}) \tag{6}$$

Where α is the learning rate, which controls the step size of each iteration. By continuously iterating, the optimal solution θ^* that converges can ultimately be found.

2.4. Establishment of the SIRW Model

In this study, an SIRW model was developed by extending the classic SIR model with a Wise (W) [12] group to simulate the spread of rumors. In this model, Susceptible individuals are unaware of the rumor, Infective individuals spread it, Removal individuals stop after learning the truth, and Wise individuals debunk it. This model better represents real-world network dynamics and is defined by following differential equations:

$$\begin{cases} \dfrac{dS(t)}{dt} = -\alpha S(t)I(t) - \beta S(t) - xS(t)W(t) \\ \dfrac{dI(t)}{dt} = \alpha S(t)I(t) - \gamma W(t)I(t) - zI(t) \\ \dfrac{dR(t)}{dt} = \gamma W(t)I(t) + xS(t)W(t) - yR(t) + zI(t) \\ \dfrac{dW(t)}{dt} = yR(t) + \beta S(t) \end{cases} \tag{7}$$

In the equations, $S(t)$, $I(t)$, $R(t)$ and $W(t)$ represent the number of users in the Susceptible, Infective, Removal, and Wise populations at time t, respectively. The differential equations describe the following probabilities: α denotes the probability of Susceptible individuals transitioning to Infective, β represents the probability of Susceptible individuals becoming Wise, γ indicates the probability of Infective individuals becoming Removal, x signifies the probability of Susceptible individuals becoming Removal, y describes the probability of Removal individuals becoming Wise, and z represents the probability of Infective individuals transitioning to Removal.

2.5. BA Scale-free Complex Network

The BA scale-free network model, commonly used for real-world complex systems such as the Internet and social networks, is characterized by a power-law degree distribution. It is generated by two main processes: network growth, starting with a few nodes and adding new ones over time, and preferential attachment, where new nodes preferentially connect to those with more connections. The attachment probability is directly proportional to the existing node's degree, mathematically represented as:

$$\Pi(k_i) = \frac{k_i}{\sum_j k_j} \tag{8}$$

Where $\sum_j k_j$ represents the total degree of all nodes in the network. According to this mechanism, nodes with higher degrees attract more connections, gradually resulting in a network structure where a few high-degree nodes coexist with a large number of low-degree nodes.

The degree distribution $P(k)$ of the network satisfies the following relationship:

$$P(k) = \frac{d}{dk}\left(\frac{m^2}{k^2}\right) \sim k^{-3} \tag{9}$$

Thus, the degree distribution of the BA scale-free network follows a power law. This indicates that most nodes have a small degree, while a few nodes have a very high degree. This power law characteristic has been observed in many real-world networks.

2.6. Application of the SIRW Model in BA Networks

The SIRW model's differential equations apply to uniformly distributed individuals, necessitating a probabilistic model for network topology adaptation. The model's details are as follows:

$$P_{SI}(V) = \frac{\alpha N_{VI}}{K_V} \tag{10}$$

$$P_{SR}(V) = \frac{x N_{VR}}{K_V} \tag{11}$$

$$P_{SW}(V) = \frac{xN_{VW}}{K_V} \tag{12}$$

$$P_{IR}(V) = \min\left\{\frac{\gamma N_{VW}}{K_V}, \frac{zN_{VR}}{K_V}\right\} \tag{13}$$

$$P_{RW}(V) = \frac{yN_{VW}}{K_V} \tag{14}$$

Here, V is a node in the network that is in a certain state, K_v represents the degree of this node and $P_{SI}(V)$ denotes the probability of this node transitioning from state S to state I. N_{VI} refers to the total number of neighboring nodes in state I. When the node V transitions from state I to state R, it is simultaneously influenced by neighboring nodes in states R and W, which can be simplified by taking the minimum of the two probabilities. The meanings of other formulas follow similarly.

2.7. Robustness Analysis

Robustness analysis of BA networks mainly examines network connectivity and stability against random failures or targeted attacks. It involves analyzing the network's degree distribution, which follows a power law:

$$P(k) \sim k^{-\gamma} \tag{15}$$

Here, $P(k)$ represents the probability of a node having degree k, and γ is typically close to 2. This characteristic allows BA networks to exhibit different robustness behaviors in response to node failures.

To quantify the robustness of the network, we define the size of the remaining connected components as an indicator of network connectivity:

$$S = \frac{N_c}{N} \tag{16}$$

Here, N_c represents the number of nodes in the largest connected component, and N is the total number of nodes. This metric reflects the changes in connectivity following node failures.

Additionally, the average path length of the network after an attack can also be used to assess the robustness of its topology, defined as:

$$L = \frac{1}{N(N-1)} \sum_{i \neq j} d_{ij} \tag{17}$$

Where d_{ij} represents the shortest path length between nodes i and j.

3. Experiment

3.1. Distributed Spider Based on Scrapy

Due to the robust anti-scraping mechanisms on Sina Weibo's desktop and mobile versions, we developed a crawler specifically for the mobile touch version. Initial use of Beautiful Soup and Requests slowed our scraping speed and limited data volume, prompting a switch to a distributed crawler based on the Scrapy framework. We implemented anti-anti-scraping techniques, including using Selenium for Weibo login to obtain and save cookies. To prevent bans from frequent use of the same browser and IP address, we randomly selected browsers and changed IP.

We gathered trending topics related to "starch sausage" by selecting eight highly relevant ones from previous lists and then crawled high-traffic posts, resulting in a total of 9,823 posts as of March 31, 2024. After filtering for popularity, we retained 43 valid posts, classifying them as "rumor posts" and "debunking posts." Additionally, we scraped comments on these posts, including account IDs, content, secondary comments, and timestamps, yielding 10,193 valid entries stored in a MySQL database. To ensure accurate text analysis, we cleaned the data by removing duplicates and irrelevant information, such as ads. Subsequently, Chinese word segmentation was performed, and stop words were removed using the Jieba module in Python as a preprocessing step for sentiment analysis.

3.2. Sentiment Analysis Model Based on GRU

This study implements a sentiment analysis model based on Gated Recurrent Units (GRU) to assess the sentiment tendencies of Weibo comments. Using a Weibo comments dataset as the training set, we first convert vocabulary index sequences into word vectors through an embedding layer. We then initialize the GRU's hidden states and input the word vectors to obtain hidden state outputs over time. These outputs are mapped to sentiment classification labels using a fully connected layer, with a Sigmoid function applied to generate probability values for each label. The final output is the sentiment score for each comment, indicating its probability of belonging to a specific sentiment category. Results for some texts are shown in Table 1.

Table 1. Sentiment Analysis Results of Selected Texts (Using Comments from Rumor Posts as Examples)

Id	Comment	Time	Sentiment tendency vale
1	The starch sausage might be wrongly accused, but honestly, I find it quite off-putting. There are too many additives, although they are within the safety testing limits.	2024-3-26 6:18:00	0.0006
2	"Unhealthy" can be said directly, but it shouldn't be twisted to imply that it has quality issues or that it's fake.	2024-3-26 8:24:00	0.0007
3	The raw materials are even worse than pet food...	2024-3-16 7:12	0.9989
4	Luckily, I don't like eating this stuff.	2024-3-15 20:07	0.9225

For the extracted text data, we first sort the processed comments in ascending order by date and then input them into the model for calculation. The specific process involves sorting the preprocessed comments by publication time, followed by calculating the sentiment tendency value. If the sentiment value is greater than 0.75, the text is classified as positive; if less than 0.35, it is classified as negative; and values between 0.35 and 0.75 are considered neutral.

3.3. Subsequent Processing and Parameter Optimization

In the subsequent processing stage, we classify positive sentiment rumor posts and negative sentiment debunking posts into the I compartment; negative sentiment rumor posts and positive sentiment debunking posts into the R compartment; and neutral posts into the S compartment. We then crawl the homepages of users in the R compartment to verify if they published debunking posts within the specified timeframe. If they did, they are classified into the W compartment (initially set at 50, reflecting that about 1% of the population is W). Finally, we organize and sort the data from each compartment by time, starting from 18:00 on March 15, 2024, and taking hourly time slices until 24:00 on March 31, 2024, to tally the cumulative compartment populations. Some results are shown in Table 2.

Table 2. Changes in Population Across Four Compartments of the SIRW Model (First Five Hours)

Serial number	S	I	R	W
1	9281	33	0	50
2	9252	52	8	52
3	9115	182	13	54
4	8935	352	20	57
5	8767	516	23	58

After completing the data processing, we will consider using the least squares method to solve for the undetermined parameters in the SWIR model differential equations. Based on Table 2, we create a matrix for observation and comparison, with column vectors representing the specific counts of S, I, R, and W at the same time. Drawing from the known SIR infectious disease model and real-world conditions, we assign the following initial values to the parameters involved in the calculations: $\alpha_0 = 0.30$, $\beta_0 = 0.05$, $\gamma_0 = 0.05$, $x_0 = 0.05$, $y_0 = 0.05$, $z_0 = 0.10$.Using this set of initial values, we apply the least squares method to solve for the optimal values.

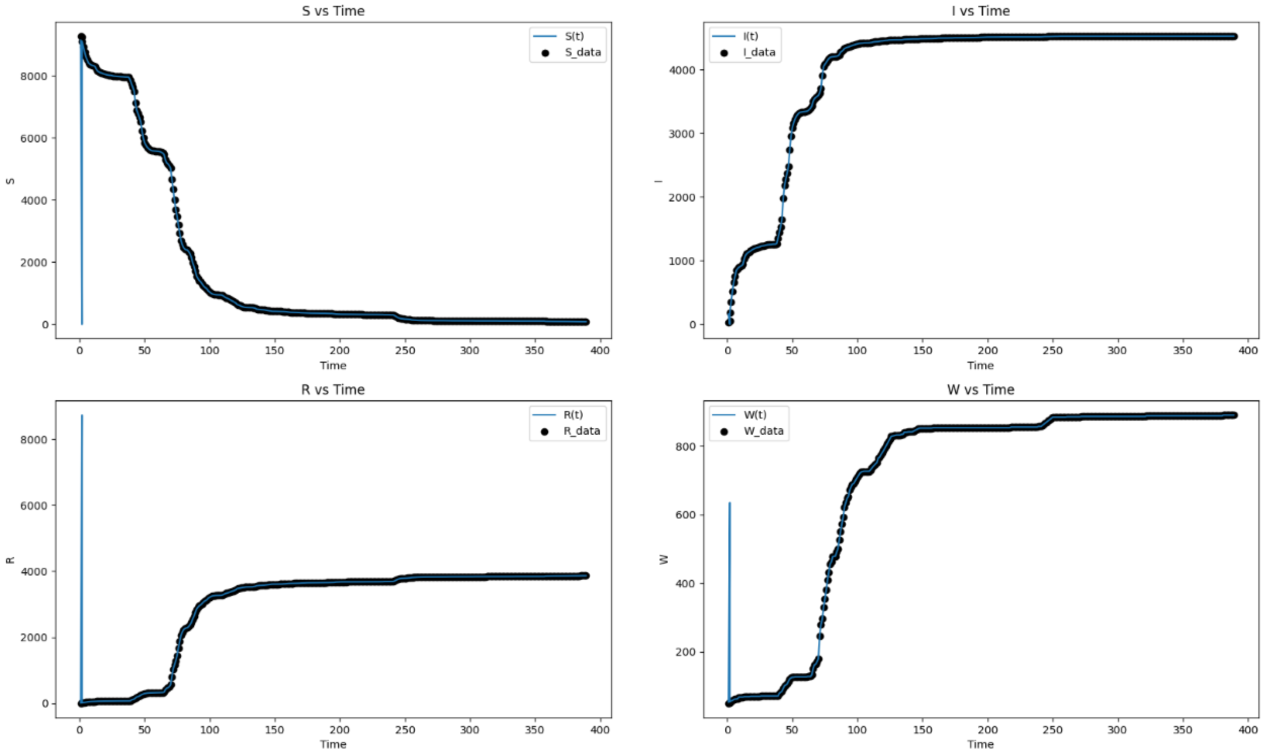

Figure 2. Least Squares Fitting Results Plot

The fitting results of the differential equations to the observed data under optimal parameter conditions are shown in figure 2. We plotted the curves of S, I, R, and W counts over time, with the blue curves representing the solutions of the differential equations and the black dots representing the observed data. Clearly, the blue curves align well with the black data points. The specific parameter values obtained from this method are as follows: $\alpha = 0.6174$, $\beta = 0.1840$, $\gamma = 0.3385$, $x = 0.0996$, $y = 0.1413$, $z = 0.3612$.

3.4. Simulation Experiments Based on BA Scale-free Complex Networks

The interpersonal relationships on the Weibo platform form a complex social network, where users' influence varies based on their engagement and follower counts. Most users have limited influence, while a few have a large number of followers, significantly impacting information dissemination. This structure follows a power law distribution, allowing us to view Weibo as a complex network composed of nodes and edges.

By integrating the established SIRW differential equations with the previously described probabilistic model into the BA network, we obtained the experimental network results shown in Figure 3, along with the corresponding curve graph in Figure 4.

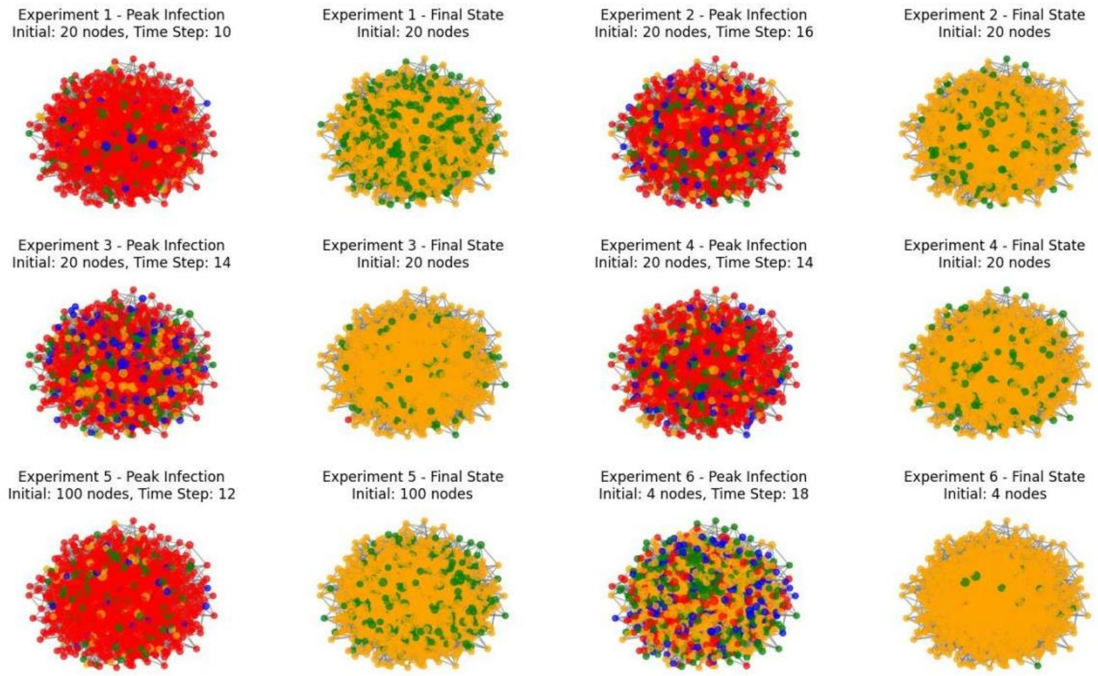

Figure 3. Experimental Simulation of Complex Networks

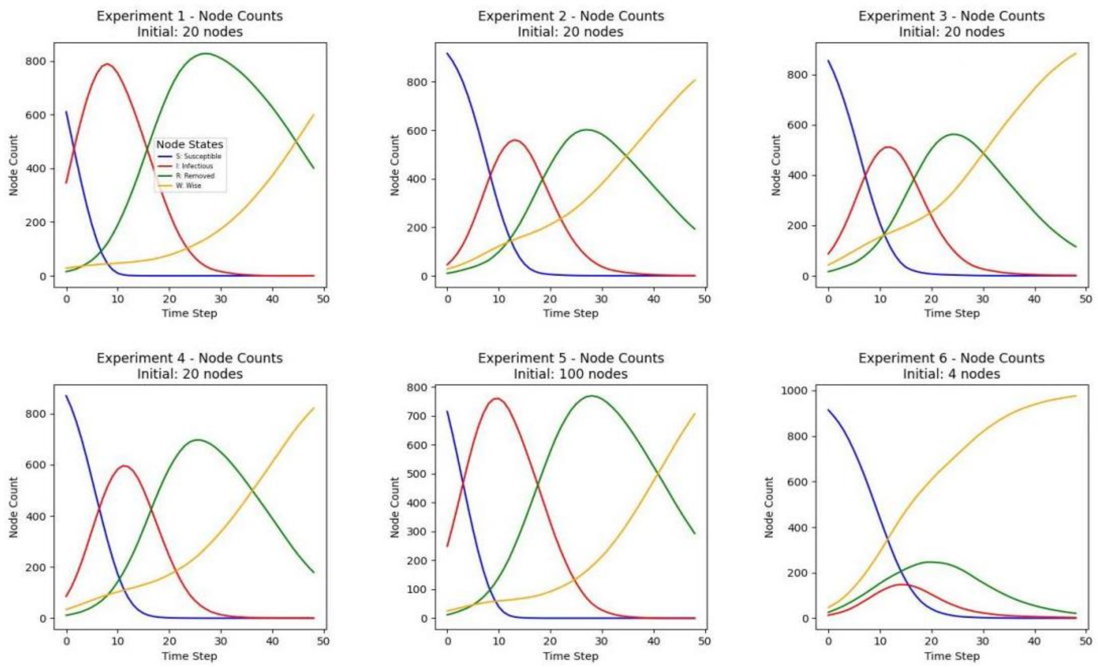

Figure 4. Experimental Results Curve Graph

In Experiments 1 to 4, the initial number of infected nodes is set to 20, with degree ranges from the top 15%–10%, 35%–30%, 55%–50%, and 75%–70% of node degrees. In Experiments 5 and 6, this number changes to 100 and 4, respectively.

Comparing the network graphs, we see that as the degree of initial infected nodes decreases, the peak of the I population declines and the time to reach this peak increases, as shown by the red line's reduced peak and the rightward shift on the x-axis. By the end of Experiment 1, the W population is noticeably sparser than in other experiments, reflected in the yellow and green lines' positions. The curve graphs indicate that in the first four experiments, the S population quickly declines, the I population rises to a peak and then falls, while the R population grows slowly at first, accelerates after the I peak, and then declines. The W population initially grows slowly but accelerates as R peaks, eventually surpassing it to become the majority. The R population peaks later than I but is slightly higher. As the initial node degree decreases, the areas between the I and S curves and between the R and W curves decrease, while the area between the I and R curves increases.

In Experiment 5, the I curve's peak significantly rises and occurs earlier, while the W population's final proportion decreases. Experiment 6 shows notable differences from Experiment 4, with the I peak very low, failing to exceed the W, S, and R populations simultaneously, and the time to reach the I peak is delayed. The curves for W, R, and I do not intersect, resulting in a large proportion of the W population.

3.5. Robustness Analysis

After simulating the user relationship network of the Weibo platform using a BA scale-free complex network, we proceed to perform a robustness analysis on our proposed complex network model. As discussed earlier, the user relationship network on the platform, similar to the BA network, adheres to a degree centrality distribution, reflecting the characteristics of a power-law distribution.

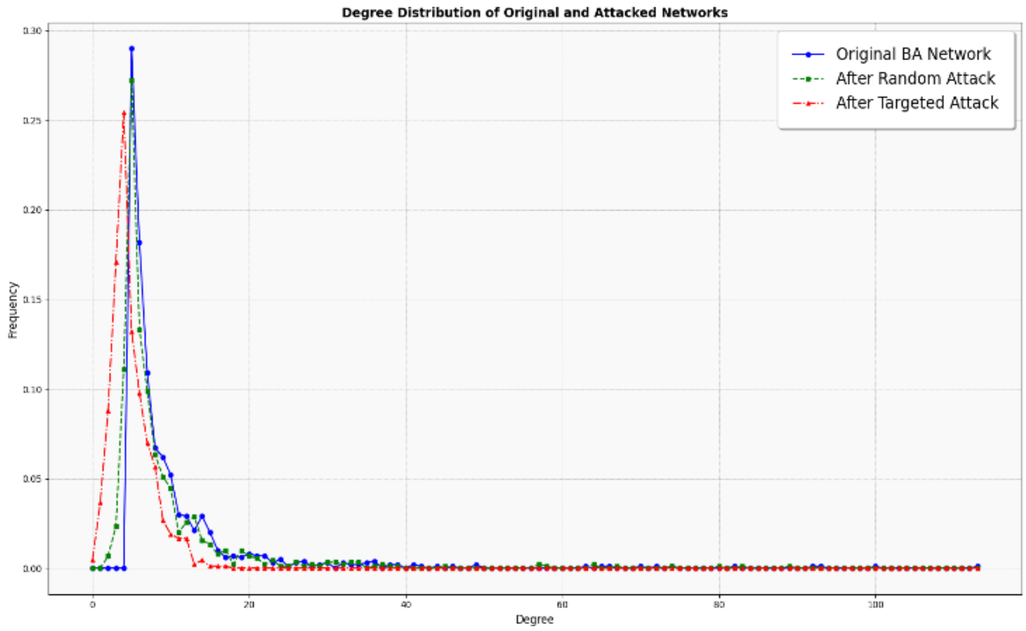

Figure 5. Effect of Bridge Node Attacks Plot

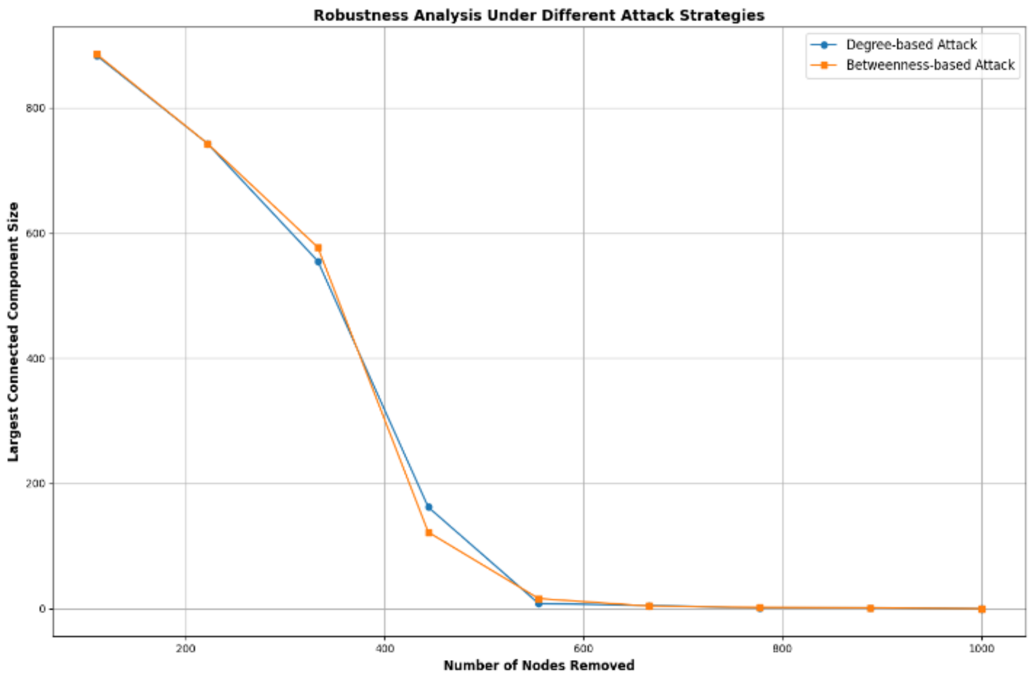

Figure 6. Comparison of the Effects of Two Attack Strategies

We now consider two types of representative nodes in the network: hub nodes and bridging nodes. Hub nodes, with high degree centrality, possess strong information dissemination capabilities, while bridging nodes act as intermediaries, connecting multiple communities and facilitating information flow between them.

We first conducted random and targeted attacks on the hub nodes. The targeted attacks significantly reduced the size of the network's largest connected component, outperforming random attacks. Next, we performed similar attacks on the bridging nodes, as shown in Figure 5. Analysis of the curves indicates that the green curve decreases relative to the blue curve, but its peak's x-coordinate remains nearly unchanged. In contrast, the red curve shifts left compared to the blue and green curves, suggesting that after targeted attacks on bridging nodes, the frequency of low-degree nodes increases, while the frequency of high-degree nodes decreases significantly, leading to a substantial decline in the network's largest connected component.

To compare the two attack strategies, we plotted their effects in Figure 6. The curves are nearly overlapping, indicating that the effectiveness of both attack types is quite similar.

Based on the analysis of the simulation results, it is evident that the S population exhibits low discernment and is easily influenced by rumors. The I population grows slowly initially, but under suitable conditions, it rises rapidly, with the peak value being related to the number and degree of information sources. The peak of the R population occurs slightly higher than that of the I population but appears later. The W population increases with the development of the event, and its initial proportion impacts rumor propagation. The W population affects the dynamics of the S, I, and R populations; the larger the initial proportion of the W population, the more difficult it is for rumors to spread. The dissemination of rumors increases both the proportion and number of the W population. Targeted attacks on bridge and hub nodes have similar effects, with purposeful attacks being more effective than random ones. Purposeful attacks have a significant impact on highly connected nodes, while random removals have minimal effect on the overall degree distribution.

4. Conclusion

This paper proposes the SIRW model to study the patterns of rumor propagation on the Weibo platform and elaborates on the differential equations characterizing this model. Time series data were collected using web scraping technology, and a GRU-based sentiment analysis model was trained to assess the sentiment orientation of user comments. Based on the least squares theory, we calculated the optimal parameters of the model and simulated the SIRW model using BA complex networks. Finally, we conducted robustness analysis of the proposed model. Through the analysis of experimental results, we identified key factors influencing the spread of rumors and provided recommendations for effectively blocking their propagation.

To effectively prevent the spread of rumors, we recommend the following strategies: In the rumor prevention stage, enhance users' ability to discern information and amplify the influence of wise users. Regulatory bodies should monitor high-impact users, conducting content reviews and educational activities. During the dissemination phase, rational users should actively engage in debunking rumors, while social platforms should promptly issue refutation statements and, if necessary, restrict dissemination. In the cleanup stage, classify and adjust the propagation process, and establish a credibility points system to encourage rational behavior.

In our study, Weibo user comments were classified, but this may not fully reflect their true sentiments due to the use of popular expressions and sarcasm. Single comments may also fail to capture dynamic attitudes over time. Relying solely on rumor-refuting posts to identify the W population is insufficient and lacks comprehensive coverage. While the rumor propagation model offers some insights, network simulations need to be repeated, and data processing is idealized and not reflective of real environments.

In the future, our user analysis will incorporate behavioral data such as likes and shares to create a more comprehensive user profile. Additionally, we will incorporate context analysis, considering the timing and topics of comments to capture sentiment changes. Surveys or questionnaires will be added to improve research accuracy, and users will be classified based on long-term behavior to analyze their interaction relationships with network users. We aim to construct more precise models, improve data acquisition methods, refine model parameters, and explore effective blocking mechanisms. By employing more scientific methods to obtain data and analyzing the differences in key parameters, we can establish social network prediction models that better reflect real-world conditions. This will allow for the early control of critical nodes during rumor propagation and enable the implementation of more effective blocking strategies, thereby promoting the healthy development of the network.

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