Introducing Individual Biases, Trust, and Information Freshness for Competitive Information Diffusion Model in Social Networks

Abstract

This paper analyzes information diffusion, focusing mainly on competitive information within social networks. We introduced realistic factors, namely, the polarity of an individual towards a particular information, the level of trust between persons, and the decaying freshness of information in the network. We presented a model by incorporating these factors with the Susceptible-Infected-Recovered (SIR) model as a basis. We developed a web-based interface to simulate the model on user-uploaded graphs. The application simulates the spread of information based on the values of the user-defined parameters and generates a comprehensive visual report. Provision for simultaneously submitting multiple simulation jobs is also created. We reported experimental results on several synthetic and real-world networks using the developed simulation platform.

CCS Concepts

• **Do Not Use This Code → Generate the Correct Terms for Your Paper**; *Generate the Correct Terms for Your Paper*; Generate the Correct Terms for Your Paper; Generate the Correct Terms for Your Paper.

Keywords

SIR Model, Information Propagation, Simulation, Social Network Analysis, Network Science

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1 Introduction

Social networks have been at the forefront of spreading information to mass by means of word-of-mouth. This has been widely studied under the application of viral marketing [5, 8, 21, 24, 28], influence maximization [6, 14, 20, 26, 38, 40, 42], top-k influential nodes [1, 15, 36, 41], epidemic modeling [11, 13, 27, 32] and many other related research exploration [9, 19, 23, 33, 35, 37, 38]. In many cases, multiple conflicting information is propagated simultaneously in the network. For example, information about two similar products of different brands is shared in the network, or two counter-narrative information are shared, such as political campaigning. It is important to model such scenarios and identify the spreading agents therein. Measuring the spread of the information over the network is also important. The majority of the existing work on information spreading considers singular information spread. Diffusion models such as the Independent Cascade Model (ICM) [7, 39], Linear Threshold Model (LTM) [12], and Susceptible, Infected and Recovery (SIR) [30] models are some of such information-spreading models. There are very few models that use conflicting information as consideration. For example, the Competing Cascade Model (CCM) [31] addresses the dynamics of conflicting information by allowing multiple pieces of information to spread simultaneously and compete for influence within the network. In this model, nodes can be influenced by various sources, but ultimately adopt information from the source with stronger influence or more significant presence [18]. Similarly, the Susceptible-Infectious-Cured (SIC) propagation model [34] investigates how conflicting information interacts over time, emphasizing the temporal aspects of information conflict and resolution. Another relevant model proposed in [17], explores how contradictory information spreads and interacts, providing information on the mechanisms that drive the acceptance or rejection of conflicting messages within a social network.

The study of competitive information diffusion is particularly interesting, where two or more conflicting pieces of information compete for attention and adoption within a social network. This phenomenon is widespread across different fields, including marketing, politics, and public health, where competing products, ideologies, or health behaviors are promoted simultaneously. Understanding the factors determining the level of importance of one piece of information over another is essential for developing effective information dissemination and influence strategies. Analyzing conflicting information spread in social networks helps us understand initial spreaders, information properties, and network structure communities with strong internal connections can favor one piece of information over another, such as connectivity, centrality, and clustering, which are crucial for understanding the behavior of these networks [2].

Contribution: Our work incorporates some of the realistic factors those were ignored in previous attempt in modeling competitive information diffusion in social networks. By extending the SIR model and incorporating realistic factors, such as individual biases, trust between individuals, and the freshness of information, it offers valuable insights into the complex dynamics of information spread in online environments.

This present paper begins by presenting the related work in Section 2 followed by the proposed model in Section 3. Section 4 presents the GUI tool developed for the evaluation and Section 5 reports the experiments and results. Finally, in Section 6, we concluded the research outcome with a discussion on possible future extensions possibility.

2 Related Work

The Susceptible-Infected-Recovered (SIR) model, initially proposed by Kermack et al. in [16] to study the spread of infectious diseases,

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has been widely adapted to model information diffusion in social networks. In this context, individuals can be in one of three states: susceptible (those who have not yet been exposed to the information), infected (those who have adopted and are spreading the information), and recovered (those who have lost interest in spreading the information). While the traditional SIR model provides a valuable framework for understanding information diffusion, it often assumes a homogeneous population, where all individuals have the same probability of adopting and spreading information. However, real-world social networks are heterogeneous, with individuals exhibiting diverse behaviors and preferences. To address

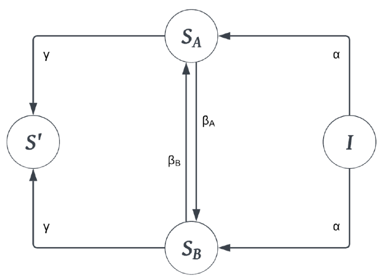


Figure 1: State Diagram for the M-SIR Model [10]

this limitation, Beutel et al. [4] extend the SIR model by introducing the concept of partial competition between two viruses. Unlike the traditional SIR model, which typically addresses the spread of a single virus, their model allows for the simultaneous spread of two viruses that provide partial immunity to each other. Liu et al. [25] enhance the SIR model by adding a new state called 'Hesitated', resulting in the SHIR model. This state represents individuals who are undecided about which information to adopt, effectively capturing the real-world phenomenon of hesitation or indecision when faced with competing information. Zhuang et al. [43] further advanced the SIR model into the IS1S2R model, which accommodates cooperative and competitive interactions between different pieces of information. Fu et al. [10] proposed a modified SIR model that incorporates a heterogeneous population, dividing individuals into innovators, ordinary individuals, and laggards, each with different probabilities of adopting and spreading information. They introduced 4 possible states in the Modified-SIR (M-SIR) for each individual: ignorant (I), spreader $A(SA)$, spreader $B(SB)$, and stifler (S'). The state diagram for the individual in the M-SIR is shown in Figure 1. The rule for an individual spreading information over social networks according to this model can be described as follows:

(1) Originally, some seeds in the population carry information A and B, respectively, while others individual are ignorant.
(2) The ignorant individual turns into a spreader of A(or B) with probability α when they interact with another spreader of A(or B); otherwise, they will keep their ignorant state unchanged.
(3) The spreader of A(or B) may change its state to spreader of B(or A) with probability β_A (or β_B) when it interacts with spreader of B(or A).
(4) A spreader may lose interest in both information A and B and eventually become a stifler with probability γ.

The dynamics of competitive information diffusion using this model focus on the influence of innovators and network topology on the spread of two competing pieces of information. However, this method does not incorporate individual biases towards the information being propagated, the level of trust between individuals, and the decaying freshness of information over time. These factors are important, specifically with the information of competitive natures. This motivates us to develop a new spreading model for competitive information diffusion that is more realistic in nature.

3 The Model

3.1 Network Structure

The network structure is represented as a graph $G = (V, E)$. We consider a graph consisting of N nodes, each representing an individual in the network. These nodes are indicated by $V = \{0, 1, \dots, N-1\}$, and the set of edges in this network is denoted by $E \subseteq V \times V$. Each of these edges is a link between two nodes, and we can also define the set of neighbors for a node $i \in V$ as $N_i = \{j \in V \mid (i, j) \in E\}$. We simulate the diffusion of competitive information on this social network by randomly choosing some spreaders of information A and B. Other individuals are exposed to two types of information and have the choice to adopt (and consequently spread) it or ignore it. The spread of information follows the rules describe below.

3.2 Node Properties and Transition Probabilities

In our model, there are three possible states for an individual. These are ignorant (I), spreader (S), and stifler (S'). In addition, we divide the population into three subgroups: innovators, ordinary, and conservative in the similar line of [10]. This will directly affect α since an innovator would be more likely to spread information than an ordinary individual and even more likely than a conservative individual. This is determined with the help of an additional parameter $\theta \in (0, 1)$, which is chosen randomly for each individual. Then, $\alpha(\theta)$ is calculated as:

$$\alpha(\theta) = \begin{cases} \min(1, \alpha_0(1+\theta)) & \text{if innovative} \\ \alpha_0 & \text{if ordinary} \\ \alpha_0\theta & \text{if conservative} \end{cases}$$

Here, α_0 is the initial spreading rate assigned to all nodes. Similarly, θ also affects β directly, since an innovator is more likely to change the type of information that it is spreading than an ordinary person and even more likely than a conservative person. Hence, $\beta(\theta)$ is calculated as:

$$\beta(\theta) = \begin{cases} \min(1, \beta_0(1+\theta)) & \text{if innovative} \\ \beta_0 & \text{if ordinary} \\ \beta_0\theta & \text{if conservative} \end{cases}$$

Here β_0 is the initial switching rate assigned to all nodes. The above formula is used for both β_A and β_B. Apart from these spreading and switching rates, we have also considered the bias of an individual towards information A or B. For example, imagine a user whose interest supports a particular political party. If they see a post on social media claiming that their favored party has won a recent election, they are more likely to believe and share this information due to their bias. Conversely, if they come across a post suggesting that an opposing party has won, they might reject or ignore this information because it contradicts their beliefs or own bias. The modeling has been done using $\delta \in [0,1]$. If this value is 0, the individual is seen as completely biased towards information A; if the value is 1, a complete bias towards information B is exhibited by the individual. We also consider how trust between different nodes affects the change in their states. This can be illustrated in the sense that a person has various levels of trust for each source of information. We are more likely to trust a post by the official board of control for the cricket website than a random Indian cricket fan page. To model this, we use $l_{ij} \in (0,1)$, which represents the level of trust (link strength) between nodes i and j. Now that we have these parameters established, let's see how the probability of a node i changing its state from an ignorant to a spreader when it receives new information from its neighbor j is calculated: If information A is received:

$$P(\text{Ignorant} \longrightarrow \text{Spreader}_A) = \alpha(\theta) \times l_{ij} \times (1-\delta) \tag{1}$$

Otherwise, If information B is received :

$$P(\text{Ignorant} \longrightarrow \text{Spreader}_B) = \alpha(\theta) \times l_{ij} \times \delta \tag{2}$$

Thus, we can see how both bias and link strength directly affect the probability of a node s spreading a piece of information. There is one additional parameter that we have considered that directly affects the switching probability for a node, namely, data freshness. Consider a situation where a node i is in the state of Spreader $_A$, and none of its neighbors is sharing information B with it. They are only sharing information A. So when information B is shared with this node next time, it would be believed that information B is very old (state) while information A is fresh since its neighbors have been spreading information A in the recent past. Hence, the probability of switching to information B decreases. However, note that even if the node has been receiving information B and not A, the maximum probability of spreading B will be $\beta_A(\theta)$. The freshness of the information A is calculated as follows:

$$y_A = max(0, 1 - 0.01 \times (t - t_A)) \tag{3}$$

Where t_A is the previous timestamp when information A was received (may or may not have been adopted). The switching probabilities are calculated as follows:

$$\begin{aligned} P(\text{Spreader}_A \longrightarrow \text{Spreader}_B) &= \min(\beta_A(\theta), \beta_A(\theta)\times \\ &\qquad (1+\tanh(y_B - y_A))) \\ P(\text{Spreader}_B \longrightarrow \text{Spreader}_A) &= \min(\beta_B(\theta), \beta_B(\theta)\times \\ &\qquad (1+\tanh(y_A - y_B))) \end{aligned} \tag{4}$$

Since $0 \leq y_A, y_B \leq 1$, we know that $-1 \leq (y_A - y_B) \leq 1$

We chose this activation function because, in the case of $y_A = y_B$, the switching probabilities remain unaffected, as they should. When deciding whether to switch from A to B, if $y_B < y_A$, then $P(S_A \longrightarrow S_B) = \beta_A(\theta)$ note that $P(S_A \longrightarrow S_B) \neq 0$ and $P(S_B \longrightarrow S_A) \neq 0$

3.3 Stable Equilibrium

We use $I(t)$ as the number of ignorant, the number of spreaders of A as $S_A(t)$, the number of spreaders of B as $S_B(t)$ and the number of stiflers as $S'(t)$. We know that $I(t) + S_A(t) + S_B(t) + S'(t) = N$ as these are the only possible states for each node. Then,

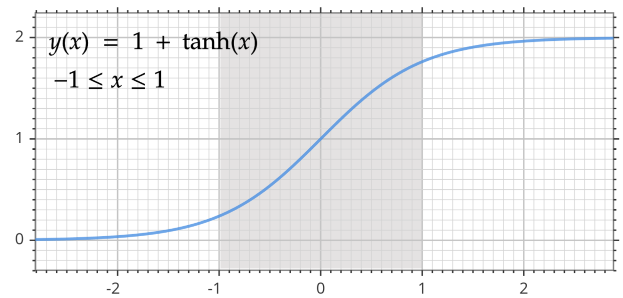


Figure 2: Function used for switching preference, based on information freshness. The gray region shows the used range.

$$\Delta I = -\alpha \frac{S_A + S_B}{N} I \tag{5}$$

$$\Delta S_A = \alpha \frac{S_A}{N} I - \beta_A \frac{S_B}{N} S_A + \beta_B \frac{S_A}{N} S_B - \gamma S_A \tag{6}$$

$$\Delta S_B = \alpha \frac{S_B}{N} I - \beta_B \frac{S_A}{N} S_B + \beta_A \frac{S_B}{N} S_A - \gamma S_B \tag{7}$$

For an effective and stable equilibrium, we set the LHS of these three equations to 0 as we do not want any change in the number of ignorant and spreaders. The condition for this equilibrium comes out to be $S_A = S_B = 0$; for example, information diffusion stops only when there are no more spreaders left in the network. Note that we have considered α, β_A, β_B and γ to be the same for each node in the network, but interestingly, the result also holds for the actual model, where each node will have its own spreading rate α and switching rates β_A and β_B.

4 Evaluation Platform

We used the Susceptible-Infected-Recovered (SIR) diffusion model as a basis and incorporated the aforementioned proposed parameters: individual biases, trust between nodes, and information freshness into it. The algorithm is shown in Algorithm 1.

4.1 GUI based Simulation Tool

We have developed a web-based user-friendly single page tool that can be used to simulate the spread of competitive information in any given network. The tool uses a client-server model. A user can upload a network and can control all the existing and proposed parameters. In addition, we provide an interface to submit multiple jobs by the user and view the results once the job is done. The simulator logic is implemented in Python, while the server-side logic uses Flask, a library designed to facilitate server-side programming. Flask handles the serving of HTML pages, which allow users to input simulation parameters and to view and analyze the results. Additionally, we use Celery, a library that enables asynchronous task execution in the background via multithreading. The workflow of the tool is illustrated in Figure 3. The client interacts with the simulator through a UX shown in Figure 3 to set the configuration of the parameters and the graph required for the simulation.

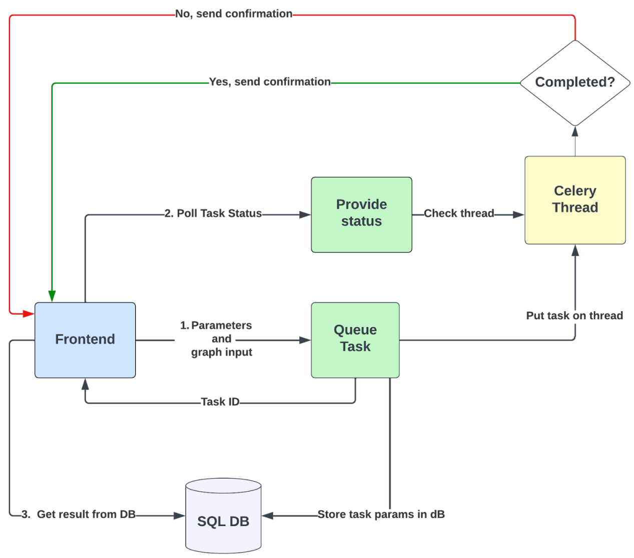


Figure 3: Simulator Workflow

Algorithm 1 Information Spread Simulation

```
Initialization of parameters for all nodes
Initialize t = 0
repeat
    for k = 1 to N do
        Choose a random node i ∈ V
        Choose a random neighboring node j which is a spreader
        if no such node exists then
            continue
        end if
        if i is ignorant then
            if j is Spreader_A then
                Update t_A for node i, i.e., latest timestamp for info A
                i becomes Spreader_A with probability P(I → SA)
                Update the number of individuals with different states
            else if j is Spreader_B then
                Update t_B for node i, i.e., latest timestamp for info B
                i becomes Spreader_B with probability P(I → SB)
                Update the number of individuals with different states
            end if
        else if i is a spreader then
            if i and j are spreaders of the same type of information then
                Update t_A (or t_B as the case may be) for node i
            else
                Calculate freshness of info A and B
                if i is Spreader_A then
                    Update t_B for node i, i.e., latest timestamp for info B
                    i becomes Spreader_B with probability P(SA → SB)
                    Update the number of individuals with different states
                else
                    Update t_A for node i, i.e., latest timestamp for info A
                    i becomes Spreader_A with probability P(SB → SA)
                    Update the number of individuals with different states
                end if
            end if
        end if
    end for
    for all spreaders do
        Spreader becomes Stifler with probability γ
        Update the number of individuals with different states
    end for
until number of spreaders becomes 0 or termination time is reached
```

After configuring the settings, the client submits these as a POST request to the server. The server processes this input by initially storing the parameters and the graph's edge list and using them to create an asynchronous Celery task instead of running the 'simulate' function immediately. The task ID is then returned to the client, and an instance containing this ID, along with the submission details, is saved in the SQL database. This instance initially has null-initialized fields for duration and results. In the back end, Celery, using Redis as a broker, manages the tasks across configurable threads, default set to four. As the task progresses, its status updates from 'PENDING' to 'SUCCESS' are reflected in the task results table. When the task completes, the server updates the SQL database entry, confirms completion and the task result table displays the final duration, changing the status to 'Finished.' The user can then access the completed results via a link marked 'Finished'. The server retrieves and displays the results on a separate page with options to download a PDF of the results in Figure 5.

5 Experiments and Result

To validate our modified SIR model and simulator, we conducted experiments on four real-world social networks:

(1) Barabási–Albert (BA) Network [3]: This is a synthetic scale-free network generated using the Barabási–Albert model, often used to model social networks due to its preferential attachment mechanism.
(2) Enron Email Network [22]: This network represents email communication within Enron Corporation. Nodes are email addresses, and edges represent email exchanges.
(3) Facebook Combined Network [22]: This network comprises "circles" or friend lists from Facebook, representing user connections.
(4) Wikipedia "Crocodile" Network [29]: This network represents a page-page network of crocodiles in Wikipedia, where nodes are articles and edges are mutual links.

For each network, we simulated the spread of two competing pieces of information (A and B) with varying parameters for spreading rate (α), switching rate (β), individual biases (δ), and trust between nodes (l_{ij}). We also considered the impact of information freshness on changing behavior. The results of our simulations are presented in the form of plots in Figure 6. It shows the proportion of spreaders, switchers, stiflers, and unaffected individuals over time. These plots reveal distinct patterns of information diffusion across different networks and parameter settings.

We have analyzed three variants of the Barabási-Albert network: the first with 100 nodes and 10 spreaders each for information types A and B; the second with 500 nodes and 50 spreaders for each type; and the third with 1000 nodes and 100 spreaders for each type. We consistently maintained the proportion of initial spreaders across all three networks to ensure comparability. We set α, β_A, β_B to 0.3 and γ to 0.2 for all the experiments. In Figure 6(a), for all network sizes, the proportion of spreaders for information A and B initially increases rapidly, indicating a quick adoption and transmission within the network during the early stages of diffusion. The proportion of spreaders peaks for each information type and then gradually declines over time, suggesting that the spread of information eventually slows as fewer susceptible individuals remain. The peak of spreaders is higher and occurs later in larger networks ($N = 1000$) compared to smaller networks ($N = 100$), showing that larger networks allow for a greater reach and more extensive spread of information, but the process takes longer due to the increased

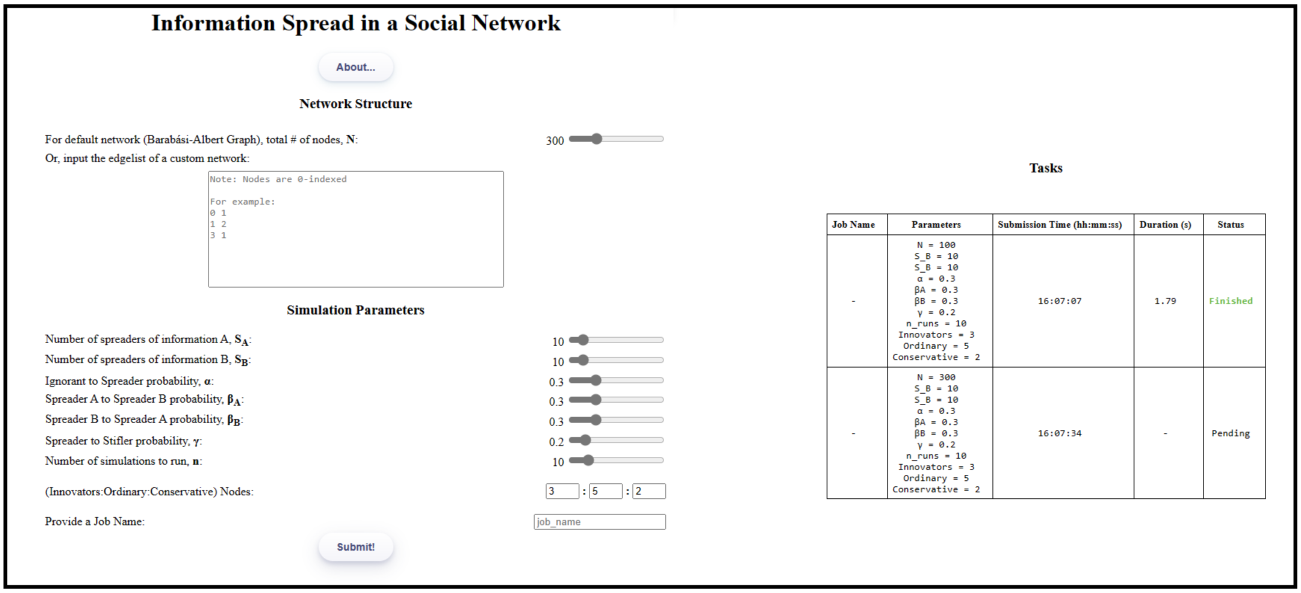


Figure 4: Simulation Application Page

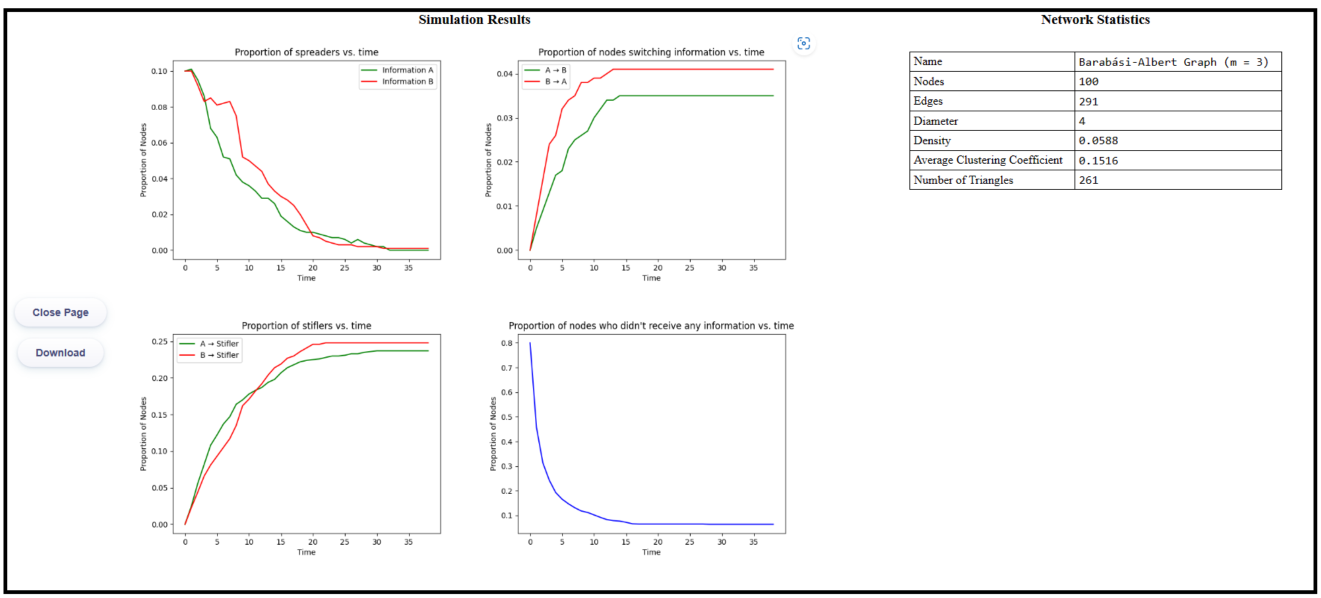
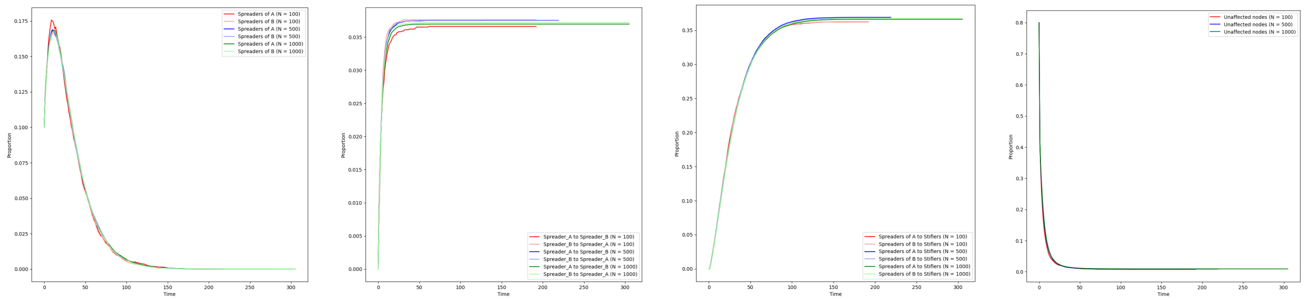


Figure 5: Simulation Result Page

number of nodes and connections. The spread of information *A* and *B* follows similar patterns, often mirroring each other, indicating a competitive dynamics where the two pieces of information compete for attention and adoption. The proportion of spreaders does not reach zero even after an extended period, suggesting that a small fraction of individuals continue to spread information, likely due to highly connected nodes in the Barabási-Albert network, which maintain and spread information over time.

Figure 6(b) switchers node for *A* to *B* and *B* to *A* remains relatively low throughout the simulation, the ratio never exceeding 0.035. This indicates that individuals are generally reluctant to change their stance on information, even when presented with competing viewpoints. This low switching rate could be attributed to individuals having strong convictions or biases towards their initial information, making them less receptive to alternative views. A slight increase in the proportion of switchers as network size grows suggests that larger networks offer more opportunities for exposure to diverse viewpoints, potentially leading to a slightly higher likelihood of switching. However, the overall low proportions indicate that even in larger networks, individuals might not



(a) Spreader

(b) Switchers Node

(c) Stiflers

(d) Unaffected Node

Figure 6: Comparison Result Albert Barabasi Network

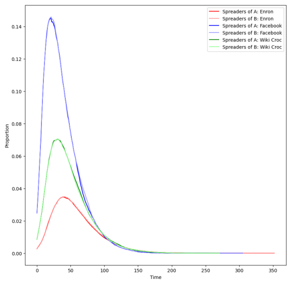
actively seek out or be exposed to diverse viewpoints. The switching patterns for A to B and B to A are generally similar, increasing initially and then stabilizing over time, indicating balanced overall switching behavior between the two types of information. The switching proportion tends to increase slightly faster in smaller networks (N=100) than in larger ones (N=500, 1000), possibly due to faster information dissemination in smaller networks, leading to quicker exposure to competing views and influencing switching decisions. Additionally, the influence of trusted connections in the network could play a role in the observed switching patterns, as individuals might be more likely to switch if they see trusted peers adopting a different viewpoint.

The proportion of spreaders transitioning to stiflers increases over time, indicating that as the simulation progresses, individuals actively spreading information eventually stop and become inactive in Figure 6(c). This transition rate is generally faster in smaller networks (N=100) compared to larger ones (N=500, 1000), suggesting that in smaller networks, information disseminates more quickly, leading to faster exhaustion of susceptible individuals and a quicker transition to the stifler state. The proportion of spreaders transitioning to stiflers seems to approach a saturation point, implying that after a certain time, the transition rate slows down significantly, indicating a state where most susceptible individuals have either adopted the information or become resistant to it. The transition patterns from spreaders to stiflers are broadly similar for both information A and B, with minor variations in timing and magnitude, suggesting consistent dynamics of information spread and cessation across different types of information. Possible interpretations include information saturation, where the increasing proportion of stiflers is due to the shrinking pool of susceptible individuals as more are exposed to the information; limited attention span, where individuals lose interest or motivation to continue sharing after a certain period; network effects, where denser connections and faster dissemination in smaller networks lead to quicker transitions; and information competition, where exposure to multiple pieces of information makes individuals less committed to spreading any particular one, increasing the likelihood of becoming stiflers.

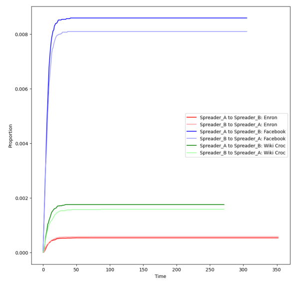
Figure 6(d) unaffected nodes decrease rapidly at the beginning of the simulation, indicating a fast initial spread of information or influence that quickly reaches a large portion of the network. The decline in unaffected nodes is steeper in smaller networks (N= 100) than in larger networks (N = 500, 1000), suggesting that information spreads faster and reaches saturation earlier in smaller networks, while in larger networks, the spread is slower and takes longer to saturate. For all network sizes, the proportion of unaffected nodes eventually reaches a plateau, implying that a fraction of nodes remains consistently unexposed to the information or influence even after a prolonged period. This could be due to various factors such as network structure, individual characteristics, or the nature of the information itself.

The simulations on Barabási–Albert networks show that network size significantly impacts information diffusion dynamics. Larger networks (N=1000) indicate delayed peaks in spreader proportions than smaller networks (N=100), indicating slower but more extensive information dissemination due to increased nodes and connections. The proportion of individuals switching between information A and B remains consistently low across network sizes. This suggests a strong influence of individual biases and trusts on information adoption. Additionally, the persistence of spreaders, even after the initial peak, underscores the role of highly connected nodes in maintaining information flow within the network. These findings emphasize the complexity between network structure and individual behavior in shaping competitive information diffusion.

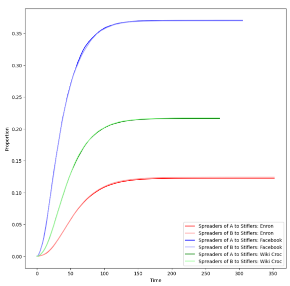
On the other hand, we can see from Figure 7(a) that because of the relatively low number of nodes w.r.t. spreaders and also the topology, the Facebook network has the highest proportion of spreaders at its peak. Also, it reaches that peak faster than the other two networks, suggesting that the relative number of spreaders to the total participants in the network has positive associativity with the amount of information spread. The interesting thing to note, though, is that the Wikipedia network manages to converge the quickest even after having almost triple the nodes as compared to the Facebook network. This might be because the Wikipedia network never managed to reach an equal proportion of spreaders w.r.t the Facebook network. The largest network of these three, Enron, took the longest to converge. Thus, information stayed in the network for the longest but was being spread by a very small proportion of participants. Figure 7(b) shows that the Facebook network has the highest proportion of participants switching from spreading one type of information to another. A very small proportion of nodes were switching information in the Enron network,



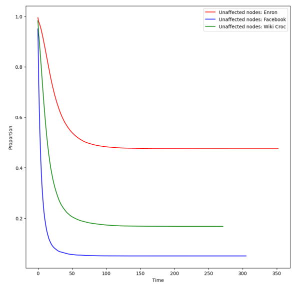
(a) Spreader



(b) Switchers Node



(c) Stiflers



(d) Unaffected Node

Figure 7: Comparison Result of Eron Email, Facebook, and Wikipedia Network

leading to the conclusion that most nodes were either ignorant or just not switching. Figure 7(c) follows the same trend as Figure 7(a) simply because the process of becoming stiflers is a probabilistic process. Also, the number of stiflers is proportional to the number of spreaders. Hence, the Facebook network has the highest proportion of stiflers, followed by the Wikipedia network and the Enron network. In Figure 7(d), we can see that almost 50% of the nodes in the Enron network never received any kind of information, showing how inefficient information diffusion is in sparse networks. Wikipedia network follows right after, having about 20% its nodes as unvisited on average in the stable state. Almost all the nodes received some information in the Facebook network (being the densest), as it had only 5% if its nodes were unvisited.

The simulation results highlight the impact of network structure on information diffusion. In sparse networks like Enron, where individuals have fewer connections, a significant portion still needs to be exposed to information. This contrasts with denser networks like Facebook and Wikipedia, where information spreads rapidly and reaches a larger audience. Interestingly, the maximum number of spreaders (actively sharing information) increases with the network's size. This suggests that larger networks offer more pathways for information to travel, potentially leading to a broader spread. However, this observation justifies further investigation to understand the underlying mechanisms. Despite these differences, all networks exhibit similar trends in the proportions of spreaders, switchers (those who change the type of information they spread), and stiflers (those who stop spreading information) over time, as can be seen in Figure 8. This suggests that while the network structure influences the speed and reach of information diffusion, the overall patterns of information spread and decay remain consistent across different types of network.

6 Conclusion and Future Work

We introduced various parameters related to human behavior in the SIR model and developed a simulation platform to understand their contribution to the spread of information. With this simulation platform, we perform experiments on various synthetic and real-world networks. We show how the structure, specifically the size of the network, affects the spreading behavior. The results are consistent across all graphs and in accordance with general social hypotheses. This simulation platform will help researchers understand the spreading process for the graph of their choice. The code will be released along with the paper. Dynamic or temporal graphs are kept for future work.

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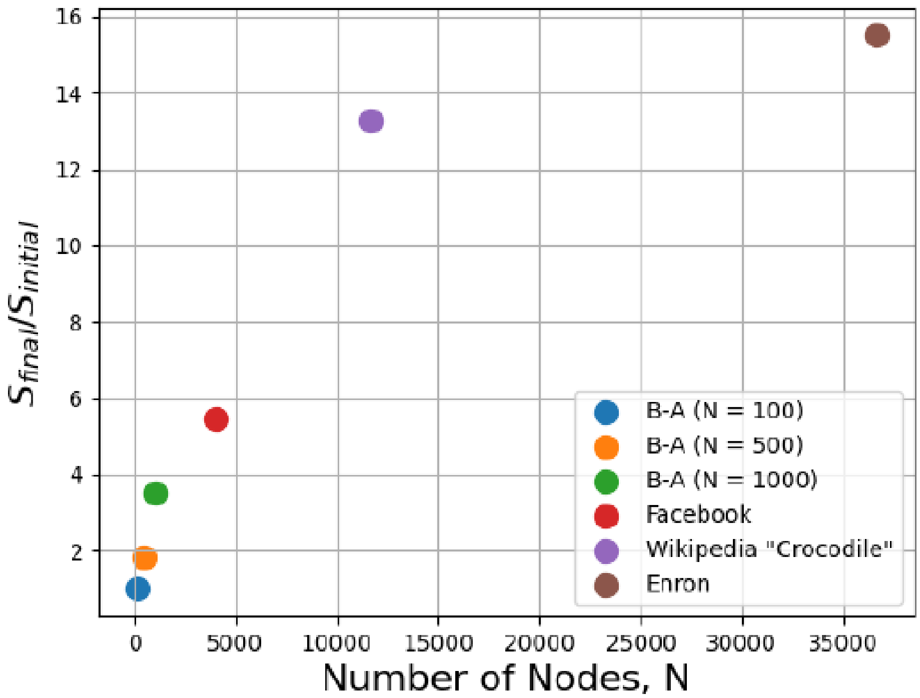

Figure 8: Trend in the increasing proportion of spreaders observed through simulations

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