Rumor Propagation Model Considering Different Propagation Probabilities in Social Networks (Postprint)

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Abstract

Regarding the analysis and control of rumor propagation in social networks, existing rumor propagation models fail to characterize the influence of different nodes on rumor propagation probability, which prevents these models from realistically describing rumor propagation in real-world social networks and consequently impairs the control of rumor propagation within networks. To address this issue, we incorporate the propagation probability of rumors between different nodes based on the SIR propagation model and analyze the influence of different nodes on this probability, thereby establishing a rumor propagation model for social networks that accounts for the inherent influence of network nodes. Finally, through comparison between the improved rumor propagation model and the commonly used SIR model, experimental results demonstrate that the proposed improved model can more rapidly control rumor propagation in networks.

Full Text

Rumor Propagation Model Considering Different Propagation Probabilities in Social Networks

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Abstract: Existing rumor propagation models cannot describe the effect of different nodes on rumor propagation probability, which prevents them from accurately capturing rumor spread in real social networks and hinders effective rumor control. To address this limitation, this paper proposes an improved rumor propagation model based on the SIR framework that incorporates propagation probabilities between different nodes and analyzes their impact. Experimental comparisons with the conventional SIR model demonstrate that the proposed model can more rapidly suppress rumor propagation in networks.

Keywords: social networks; rumor model; information spreading; propagation probability

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0 Introduction

Social networks based on the internet encompass all network services centered on human social interaction, fundamentally transforming contemporary communication and thinking patterns. While facilitating interpersonal communication, social networks also introduce the challenge of misinformation—referred to as online rumors—which spreads rapidly and disruptively. Online rumors are defined as factually baseless statements disseminated through network media, often with aggressive or purposeful intent. Their sudden emergence and rapid circulation negatively impact normal online communication.

To control rumor propagation in social networks, analyzing their spread mechanisms is essential. Rumor dynamics combines dynamical principles with mathematical methods to study how rumor prevalence evolves over time in networks. Modeling these propagation patterns represents the most common approach for rumor control. Numerous models have been developed to analyze and describe rumor propagation mechanisms, primarily focusing on social relationships within networks. For instance, reference [3] improved the CSR model' s acceptance probability mathematical framework by incorporating individual acceptance thresholds, making it more suitable for mobile SNS user behavior. Reference [4] proposed a rumor propagation model based on an acceptance probability function that accounts for dual-effect media influence, rumor acceptance signal superposition, and trust factors. Reference [5] constructed a microblog rumor propagation model based on the SIR framework that considers how dormant users can be awakened by opinion leaders.

These studies analyze rumor acceptance from the perspective of individual users, but they fail to examine how different individuals actively influence rumor propagation, thereby preventing analysis of network-wide spread patterns. Classic SIR models can abstractly describe information propagation in social networks and have been widely applied to rumor research. For example, reference [7] introduced both positive and negative infection states into the traditional rumor model based on SIR, proposing the SPNR model. Reference [8] developed an SEIR rumor propagation model for heterogeneous networks where nodes exposed to rumors may transition to removed states at certain rates. Reference [9] introduced hot propagation nodes representing high-influence users into social networks, proposing an improved SIR-based information propagation model. Reference [10] studied a rumor propagation model with skepticism mechanisms based on SIR, proposing the SIQR model and numerically analyzing how rumor-truth transmission rates affect propagation dynamics.

Although these works analyze the impact of node types on rumor propagation from various perspectives, they only address a few typical node categories and assume homogeneous propagation within each type—meaning rumors spread with identical probability between nodes of the same category. This assumption is invalid in real social networks, where different individuals (at a finer granularity than node types) typically exhibit varying propagation effectiveness. Consequently, existing models cannot accurately represent how different nodes influence propagation probability, limiting their ability to describe real-world rumor spread and impeding effective rumor control.

To address the phenomenon of varying rumor propagation probabilities between different nodes in actual social networks, this paper analyzes these probabilities based on the widely-used SIR rumor propagation model. By examining how individual nodes affect propagation probability, we establish a rumor propagation model that considers node-specific influences in social networks. Comparative experiments with the conventional SIR model demonstrate that our improved model can more rapidly control rumor spread in networks.

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1 SIR Propagation Model

The classic SIR rumor propagation model [15] typically uses three node categories to represent different individuals in social networks: Susceptible (S) nodes are unaware of the rumor; Infected (I) nodes have been influenced by and spread the rumor; and Recovered (R) nodes recognize the information as rumor and cease propagation.

In the SIR model, when an Infected node (I) contacts a Susceptible node (S), the Susceptible node becomes an Infected node with a fixed probability β. All Infected nodes in the network transition to Recovered nodes with a fixed probability . The conversion process between different node types in the SIR rumor model can be expressed as:

$$S + I \overset{\beta}{\to} I + II \overset{\mu}{\to} R$$

where the + operator indicates contact between two nodes, and I, S, R represent Infected, Susceptible, and Recovered nodes respectively.

As shown in the equations, the SIR propagation model assumes fixed probabilities for rumor propagation and recovery between nodes, which cannot represent individual differences in rumor propagation capability.

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2 Improved Rumor Propagation Model

In social dynamics, individual behavioral patterns are mostly heterogeneous—not all individuals have the same tendency to persuade others [16]. Based on this fact, we improve upon the SIR rumor propagation model by proposing a model that considers different propagation probabilities.

2.1 Improved Model Formulation

In social network rumor propagation, if an individual has not previously encountered the rumor, contact and communication with neighboring nodes may cause that individual to become a rumor spreader (transitioning from Susceptible to Infected). This probability depends directly on the influence of the nodes spreading the rumor—different spreaders result in different probabilities of the rumor being believed. Additionally, if an individual believes the rumor, the probability of recognizing it as misinformation in the next time step (transitioning from Infected to Recovered) also varies by individual.

To capture this phenomenon, our improved model incorporates the probability of nodes transitioning between types at any time t. Taking any node x in the network as an example, the transition process between the three node categories in the improved rumor propagation model is as follows:

$$S(t) \xrightarrow{1-i_x(t)} I(t) \xrightarrow{1-r_x(t)} R(t)$$

where $S(t)$, $I(t)$, and $R(t)$ represent the probabilities that node x belongs to Susceptible, Infected, and Recovered states at time t, respectively; $i_x(t)$ denotes the probability that node x remains in the Susceptible state at time t, and $r_x(t)$ denotes the probability that node x remains in the Infected state at time t.

From equation (2), if node x is in the Susceptible state at time t, it continues as Susceptible with probability $i_x(t)$ during interactions with neighbors, and becomes Infected with probability $1 - i_x(t)$. The value of $i_x(t)$ depends on the rumor propagation capability of surrounding neighbors. If node x is in the Infected state at time t, it continues as Infected with probability $r_x(t)$ in the next time step (i.e., continues believing the rumor), and becomes Recovered with probability $1 - r_x(t)$. The value of $r_x(t)$ depends on the node' s ability to identify rumors.

2.2 Propagation Probability Calculation

We now introduce two key probabilities in the improved model: the probability of remaining Susceptible, $i_x(t)$, and the probability of remaining Infected, $r_x(t)$.

During network node information propagation, each node randomly interacts with neighboring nodes. We represent this randomness uniformly by denoting the probability of node x interacting with a neighbor node y as $\frac{A_{yx}}{\sum_{y \in N(x)} A_{yx}}$, where k_y represents the interaction frequency between node y and its neighbors, and A_{yx} represents the interaction frequency between node y and node x.

For node x, the probability of becoming an Infected node depends on whether its neighbors are Infected and their propagation capability. If node x is exposed to rumor spreading by node y at time t with probability β_y, then the probability that node x does *not* become Infected due to y' s influence is $(1-\beta_y)^{\frac{A_{yx}}{k_y}}$.

If node x is in the Infected state, interactions with neighbors may cause it to stop believing the rumor if those neighbors recognize it as misinformation. We denote the probability of node x interacting with a neighbor y that can identify the rumor as $\frac{A_{xy}}{\sum_{y\in N(x)} A_{xy}}$, where k_x represents the interaction frequency between node x and its neighbors. For node x, the probability of transitioning to Recovered (i.e., no longer believing the rumor) depends on whether its neighbors are Recovered and their influence (ability to persuade spreaders to stop believing). If node x is awakened by Recovered neighbor y at time t to stop believing the rumor with probability γ_y, then the probability that node x does *not* become Recovered due to y is $(1-\gamma_y)^{\frac{A_{xy}}{k_x}}$.

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3 Simulation Verification

To validate the effectiveness of our proposed rumor propagation model, we compare it against the classic SIR model and two popular SIR-based improvements: the SPNR method from reference [7] and the HSIR method from reference [9] that considers hot propagation nodes. For convenience, we denote our proposed method as the SPSIR method.

In the simulation network, nodes represent individuals in the social network, categorized as Susceptible (S), Infected (I), and Recovered (R). For analysis simplicity, we initialize only one rumor spreader. At each time step, all nodes simultaneously interact for information propagation, with each individual influencing only one neighbor per time step. We set the rumor propagation probability β and the recovery probability μ to 0.5 for all models. For the classic SIR model, each spreader interacts with a neighbor at the fixed probability of 0.5. For the two improved models (SPNR and HSIR), the hot propagation probability and skepticism probability are set to 0.8 and 0.2, respectively. For our proposed model, we additionally define two propagation probabilities on top of $\beta = 0.5$ and $\mu = 0.5$: the probability of remaining Susceptible, I, and the probability of remaining Infected, R. We conduct two experiments with different settings:

- **Experiment 1:** Probabilities I and R for each node are randomly distributed in ranges (0.2, 0.5) and (0.8, 1), respectively.
- **Experiment 2:** Probabilities I and R for each node are randomly distributed in ranges (0.5, 0.8) and (0.2, 0.5), respectively.

Results are measured by the proportion of Recovered nodes in the entire network, indicating rumor control effectiveness. Final results represent averages over 50 simulation runs. The outcomes are shown in [Figure 1: see original paper] and [Figure 2: see original paper], where the x-axis represents interaction time and the y-axis represents the proportion of Recovered nodes.

The results demonstrate that our model considering different propagation probabilities significantly outperforms the three comparison methods in controlling rumor spread. This advantage stems from our model' s incorporation of varying propagation capabilities across different network nodes, rather than using fixed probabilities. While the other two improved methods (SPNR and HSIR) perform better than classic SIR, they show clear disadvantages compared to our SPSIR method in both experiments. This is because SPNR and HSIR only consider node types (hot propagation nodes and skeptical nodes, respectively) without capturing the detailed influence of each specific node on rumor propagation.

Specifically, when the probability of remaining Susceptible (I) is small and the probability of remaining Infected (R) is large, rumor control requires more time. In [Figure 1: see original paper], after 100 time steps, the proportion of Recovered nodes reaches 70% in our model, compared to only 55%, 40%, and 30% for SPNR, HSIR, and SIR, respectively. Conversely, when I is large and R is small, rumor control occurs more rapidly. In [Figure 2: see original paper], after 45 time steps, the Recovered node proportion reaches 80% in our model, versus only 50%, 35%, and 30% for SPNR, HSIR, and SIR. These results confirm that our model provides superior rumor control, with effectiveness proportional to the probability of remaining Susceptible and inversely proportional to the probability of remaining Infected.

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4 Conclusion

To address the problem of varying rumor propagation probabilities influenced by different individuals in social networks, this paper improves upon the SIR rumor propagation model by incorporating different propagation probabilities to describe rumor propagation dynamics. By analyzing how individual nodes affect propagation probability, we establish a rumor propagation model that considers node-specific influences. Comparative experiments with the conventional SIR model demonstrate that our improved model can more rapidly control rumor propagation in networks.

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Note: Figure translations are in progress. See original paper for figures.