

Retraction

Retracted: Information Spreading on Memory Activity-Driven Temporal Networks

Complexity

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

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Research Article

Information Spreading on Memory Activity-Driven Temporal Networks

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Information spreading dynamics on temporal networks have attracted significant attention in the field of network science. Extensive real-data analyses revealed that network memory widely exists in the temporal network. This paper proposes a mathematical model to describe the information spreading dynamics with the network memory effect. We develop a Markovian approach to describe the model. Using the Monte Carlo simulation method, we find that network memory may suppress and promote the information spreading dynamics, which depends on the degree heterogeneity and fraction of bigots. The network memory effect suppresses the information spreading for small information transmission probability. The opposite situation happens for large value of information transmission probability. Moreover, network memory effect may benefit the information spreading, which depends on the degree heterogeneity of the activity-driven network. Our results presented in this paper help us understand the spreading dynamics on temporal networks.

1. Introduction

Extensive real-data analyses revealed that social network exhibits strong temporal properties [1–3], i.e., the edges and nodes do not always exist at any time, and may vary with time. For instance, in scientist collaborative networks, two researchers may collaborate to publish a paper but rarely collaborate at every time step [4–9]. Besides, two researchers may build their first collaboration. Another example is that in the transportation network, two cities may build expressways and high-speed trains. Thus, a new edge is added. The emergence and disappearance of edges and nodes widely exist for the online social network due to the login or log out of the online platforms. Therefore, the temporal network is a widely used method to describe the social network, in which nodes represent individuals and edges stand for their relationships.

For the information spreading on temporal networks, researchers from different disciplines made great contributions [10–19]. In what follows, we first review the progress

of information spreading on social network. Different from the static networks, i.e., the network topology does not change with time, researchers found some important results [15, 20–23]. When the information is spreading on the static networks, scholars found that the existence of some hubs may eliminate the threshold point [24, 25]. Specifically, any values of information transmission probability can trigger the information spreading on social networks. Based on these results, we can understand why information can always spread on social platforms. Researchers further revealed that the network community, clustering, and degree-degree correlations could alter the spreading dynamics of information [26, 27]. In reality, sharing a piece of information is risky, and thus affirming its reality and reliability is fatal. Researchers used the threshold-based model to include this factor in the spreading dynamics, such as the Watts threshold model and other generalized models. For that threshold-based information spreading model, the phase transition of the dynamical system is always discontinuous, i.e., first-order phase transition [28]. Wang et al. [29, 30]

proposed nonredundant information spreading dynamics and revealed a transition between the continuous and discontinuous transition in the system.

When researchers studied the information spreading dynamics on temporal networks, scholars found that network temporality can suppress or promote the information spreading [1, 20, 21, 31–37]. Xue et al. proposed a mathematical model to describe a heterogeneous population, where a fraction of nodes adopts a complex contagion. They used a Markovian approach to describe the spreading dynamics. They found that the promotion or suppression of the network temporality is determined by the heterogeneities of population and degree distribution. Scholtes et al. [38] found that the non-Markovian temporal network may speed up or slow down the information spreading. Wang et al. [39] proposed a heuristic immunization strategy for information spreading and demonstrated the effectiveness of this strategy in real-world data.

For the temporal network, an essential factor is the network memory [38, 40–42], which means that edges that existed in the current time step may already occur in previous time steps. Sun et al. [43] revealed that network memory inhibits the spreading process for SIR models, in which the epidemic threshold is enlarged while the spreading size decreases. How memory affects the information spreading dynamics is an important question. To address this, we propose a mathematical model on temporal networks with memory. Then, we develop a Markovian theory for the dynamical model. Through extensive Monte Carlo simulations, we systematically investigate the dynamics. Finally, we conclude.

2. Information Spreading Model

In this section, we introduce the information spreading dynamics on temporal networks with network memory.

2.1. Activity-Driven Network with Memory. Mathematically, the temporal network \mathcal{G} can be described as $\mathcal{G} = (\mathcal{G}_1, \dots, \mathcal{G}_{t_{\max}})$, where \mathcal{G}_t represents the temporal network at time step t . For network \mathcal{G}_t , we use the temporal adjacency matrix A_t to represent the topology of \mathcal{G}_t . If $A_t(i, j) = 1$, there is an edge between nodes i and j at time t . Otherwise, $A_t(i, j) = 0$.

To build the activity-driven network with memory effect, we generalize the activity-driven model proposed in [44–46]. We build memory activity-driven network as follows.

- (i) Assign value for network size N and potential activity x_i according to a given distribution $f(x)$. In this paper, we assume $f(x)$ follows a power-law distribution. That is to say, $f(x) = \varepsilon x^{-\gamma}$, where γ is the potential activity distribution exponent, $\varepsilon = 1 / \sum_{x_{\min}}^{x_{\max}} x^{-\gamma}$, $x_{\min} = 10^{-3}$, and $x_{\max} = 0.99$. Mathematically, the larger the value of γ , the more homogeneous the degree distribution of the temporal network. Therefore, we can change γ to investigate the degree heterogeneity of the temporal network.

- (ii) Generating temporal network \mathcal{G}_t : for each node i , there are two possible ways to build edges. If node i becomes active with probability $a_i = \eta x_i$, where η is a parameter, node i forwardly connects to m randomly selected nodes. If node i is inactive, it can only receive the connections from other active nodes.
- (iii) At the end of the time step t , we delete every edge with probability $1 - \xi$. Therefore, the memory effect is induced. The higher the value of ξ , the more substantial the memory effect of the temporal network. For the case of $\xi = 0$, the temporal network is memoryless. When $\xi = 1$, the network is static.

According to the above steps, we know that the average degree of network \mathcal{G}_t is $\langle k_t \rangle = 2m\eta\varepsilon(\gamma - 1/\gamma - 2)$.

2.2. Information Spreading Model. We here adopt the information spreading model proposed in [47]. This model uses a generalized susceptible-infected-susceptible (SIS) model to describe the dynamics of information spreading. The susceptible nodes mean that they do not receive any information but may receive the information. The infected nodes represent that they have obtained the information and willing to share it with neighbors. In this model, we assume that there are two types of nodes, i.e., activists and bigots. The activists are willing to share the information with friends. Thus, we assume that they have a smaller adoption threshold $\theta_a = 1$. The bigots are less likely to accept the information. Therefore, we set those bigots with a higher adoption threshold $\theta_b > 1$. In this model, we randomly select a fraction of ω nodes as the bigots and the remaining $1 - \omega$ nodes as activists.

The information spreading dynamics evolve as follows:

- (i) Randomly selecting ρ_0 fraction of nodes to receive the information and setting the rest as susceptible nodes.
- (ii) At every time step, every infected node i tries to transmit the information to its very susceptible neighbor j with probability λ . If node j succeeds in receiving a piece of information, it would be represented by the mark +1 and the like. In this situation, we consider the state of node j . If node j is an activist, it becomes infected. If node j is a bigot, it becomes infected only when its received information is larger than θ_b .
- (iii) Every infected node becomes a susceptible state with probability γ_r .

When the infected nodes no longer exist or the spreading dynamics has run 10000 times, the dynamics ends.

3. Theoretical Analyses

To obtain mathematical analysis results on the spreading dynamics, we use a generalized discrete Markovian approach, which is inspired by Refs. [39, 48–50]. In theory, we assume that there are no dynamical correlations among the

state of neighbors. That is to say, the infection probabilities of a susceptible node from informed neighbors are dependent. At any time step t , node i can only be susceptible or infected state. Define $x_i(t) = 1$ when node i is in the infected state and $x_i(t) = 0$ when in susceptible state. The probability of node i in the susceptible and infected states is $\Pr[x_i(t) = 0]$ and $\Pr[x_i(t) = 1]$, respectively. For the sake of simplicity, we denote $\Pr[x_i(t) = 0]$ and $\Pr[x_i(t) = 1]$ as $s_i(t)$ and $p_i(t)$, respectively.

For the evolution of $p_i(t)$, we should consider two situations: the evolutions of bigots and activists, which are denoted as $p_i^a(t)$ and $p_i^b(t)$, respectively. Therefore, we have

$$p_i(t) = p_i^a(t) + p_i^b(t). \quad (1)$$

In the following, we study the evolutions of $p_i^a(t)$ and $p_i^b(t)$. For an activist, such as node i , the evolution of $p_i^a(t)$ includes two situations. On the one hand, node i is in the infected state at time step t and does not recover to susceptible state with probability $(1 - \gamma)p_i(t)$. On the other hand, node i is susceptible at time step t and gets infected by neighbors at this time step with probability $(1 - p_i(t))(1 - q_i^0(t))$, where

$$q_i^0(t) = \prod_{j=1}^N (1 - \lambda \mathcal{A}_{ij}(t) p_j(t)), \quad (2)$$

represents the probability of node i remaining susceptible at time step t . The evolution of $p_i^a(t)$ is

$$p_i^a(t+1) = (1 - \omega) [(1 - \gamma)p_i(t) + (1 - p_i(t))(1 - q_i^0(t))]. \quad (3)$$

For the bigots, the evolution of $p_i^b(t)$ is more complex. The bigots will only be infected if the information received is greater than the threshold θ_b . Therefore, we should first compute the number of information received by node i and denote $q_i^n(t)$ as n pieces of information received by node i at time step t . Using the results presented in Ref. [47], we have

$$q_i^n(t) = \sum_{\theta \subseteq \partial i, |\theta|=n} \prod_{j \in \theta} \lambda p_j(t) \prod_{j \in \partial i \setminus \theta} (1 - \lambda p_j(t)). \quad (4)$$

Until now, we have presented the expression of the evolution equations of the information spreading dynamics. In the steady state, i.e., $t \rightarrow \infty$, we have $p_i(t+1) = p_i(t)$. We denote the fraction of nodes in the infected state in the steady state as ρ , which can be computed as

$$\rho = \frac{1}{N} \sum_{i=1}^N p_i. \quad (5)$$

We use ρ as the order parameter of the system in the following numerical studies.

4. Results

In this section, we use the Monte Carlo method to study the information spreading dynamics on temporal network with memory effect. When generating the temporal network, we set the average degree of every temporal network \mathcal{G}_t with

average degree $\langle k_t \rangle = 10$. In the dynamical system, we set the order parameter ρ as

$$\rho = \frac{1}{1000} \sum_{t=t_{\max}}^{t_{\max}+1000} \rho(t), \quad (6)$$

where $t_{\max} = 5000$ and $\rho(t) = 1/N \sum_{i=1}^N p_i(t)$. We set $\theta_b = 2$. To numerically locate the steady state of the dynamical system, we compute the average values of $\rho(t)$. When the average value of variance $\rho(t)$ is smaller than 10^{-5} , the steady state of the system is reached.

In Figure 1, we first investigate the information spreading dynamics without bigots (i.e., $\xi = 0$). For different strengths of the memory effect, we find two distinct regions. When the information transmission probability λ is small, a strong memory effect suppresses the information spreading dynamics (see $\xi = 0$ and $\xi = 1$). That is to say, the temporal network is not beneficial in information transmission. However, for larger values of λ , the temporal network is beneficial for information spreading. For static networks, the network topology does change with time. The information can be accessed by more susceptible nodes for small values of λ since the giant connected cluster is larger. However, more different nodes will be connected to the temporal giant connected cluster for temporal networks and promote the information spreading for larger λ . Once the network memory effect is not strong enough, compared with the information spreading on static and temporal networks, the information is suppressed regardless of the information transmission probability. Thus, we know that the middle memory effect can suppress the information spreading.

We further investigate the information spreading on a given strength of memory effect for different values of bigots in Figure 2. We note that both the fraction of bigots and memory affect the information spreading. For a given network topology, we find that ρ increases with ω since bigots are not beneficial in transmitting the information. Besides, we note that the increase pattern of ρ versus λ is different for distinct values of ω . When $\omega = 0$, ρ increases continuously with λ . However, ρ discontinuously increases with λ when ω is large (e.g., $\omega = 1.0$ in Figures 2(b)–2(d) and 2(f)).

The network memory effect may benefit the information spreading, which depends on the degree heterogeneity of the activity-driven network. When the potential exponent is $\gamma = 2.1$ and 3.5, the network memory effect suppresses the information spreading (Figures 2(a), 2(c), 2(d), and 2(f)). However, when the potential exponent is $\gamma = 3.0$, the network memory effect promotes the information spreading, as shown in Figures 2(b) and 2(e).

Finally, we investigate the phase transition of the system with different initial seed sizes in Figure 3. Generally speaking, the phenomena are the same as those stated in Figure 2. We find that the system always has a hysteresis loop no matter what value ω and γ is assigned. In more detail, the final information spreading size ρ depends on ρ_0 . The larger ρ_0 , the higher ρ in the hysteresis loop region. We also note that the larger ω , the smaller ρ . That is to say, the bigots hinder the information spreading dynamics.

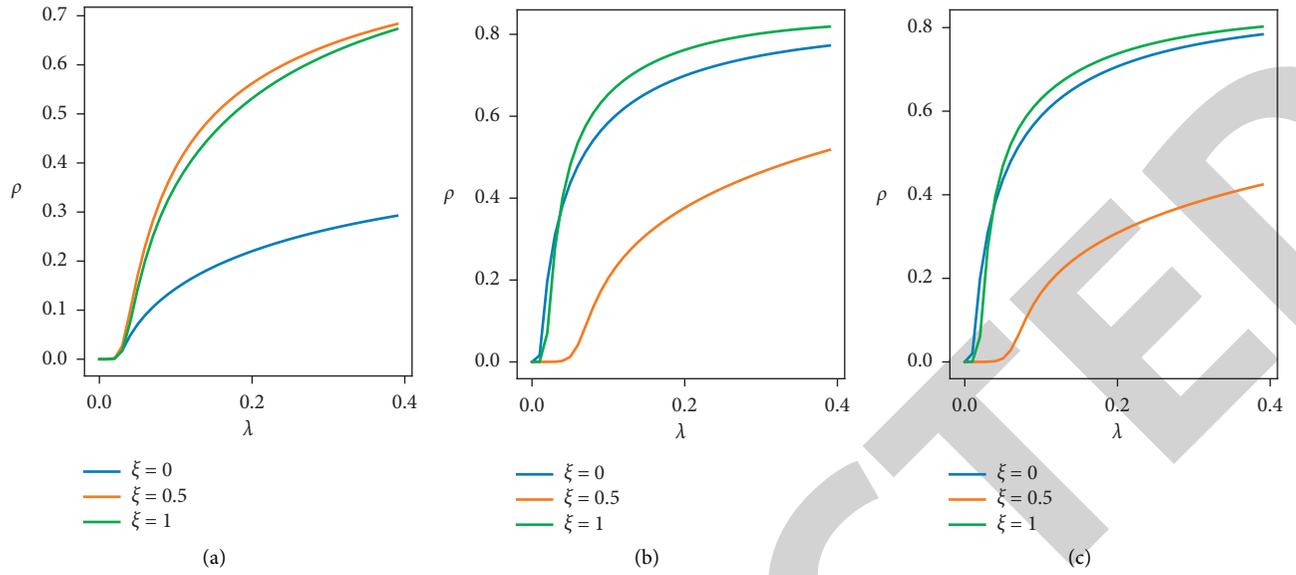


FIGURE 1: Information spreading on activity-driven networks. The final information spreading size ρ versus information transmission probability λ with $\gamma = 2.1$ (a), $\gamma = 3.0$ (b), and $\gamma = 3.5$ (c). We set the fraction of seeds as $\rho_0 = 0.1$ and the average degree as $\langle k_t \rangle = 10$, and there are no bigots (i.e., $\omega = 0.0$).

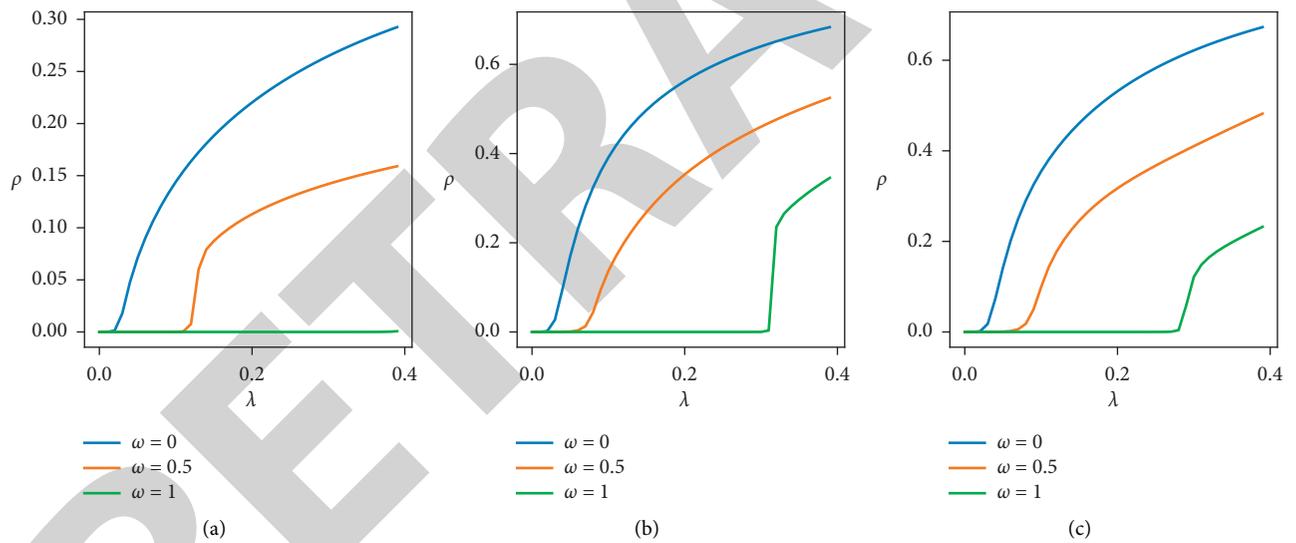


FIGURE 2: Continued.

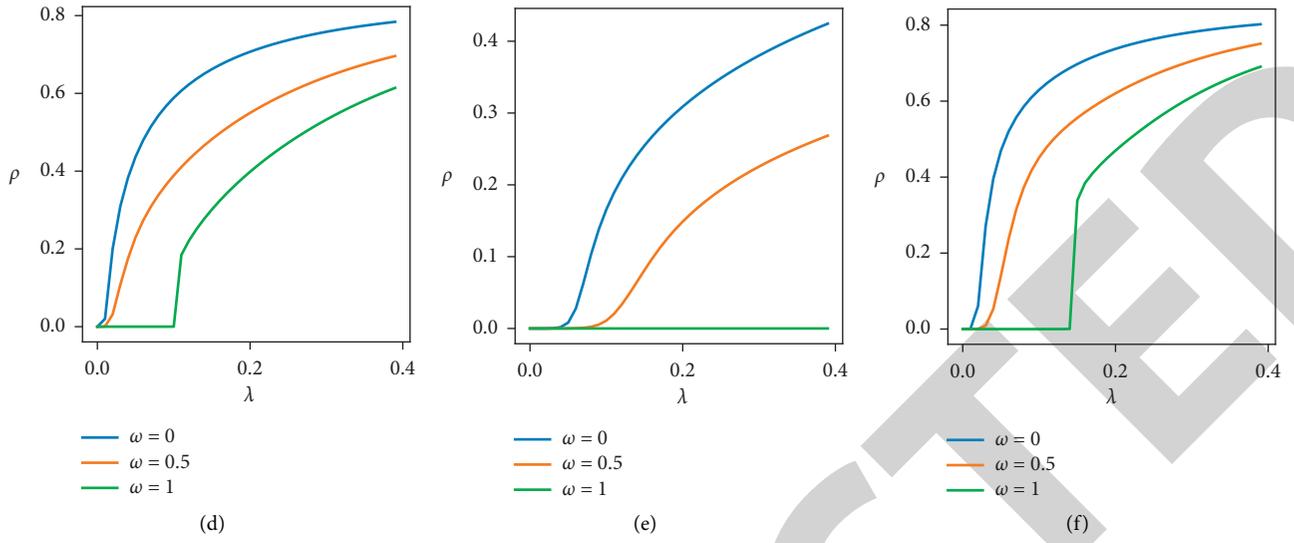


FIGURE 2: Information spreading on activity-driven networks. The final information spreading size ρ versus information transmission probability λ with $\gamma = 2.1$ (a), $\gamma = 3.0$ (b), and $\gamma = 3.5$ (c) for $\xi = 0.5$. ρ versus λ with $\gamma = 2.1$ (d), $\gamma = 3.0$ (e), and $\gamma = 3.5$ (f) for $\xi = 0$. We set $\rho_0 = 0.1$ and $\langle k_t \rangle = 10$.

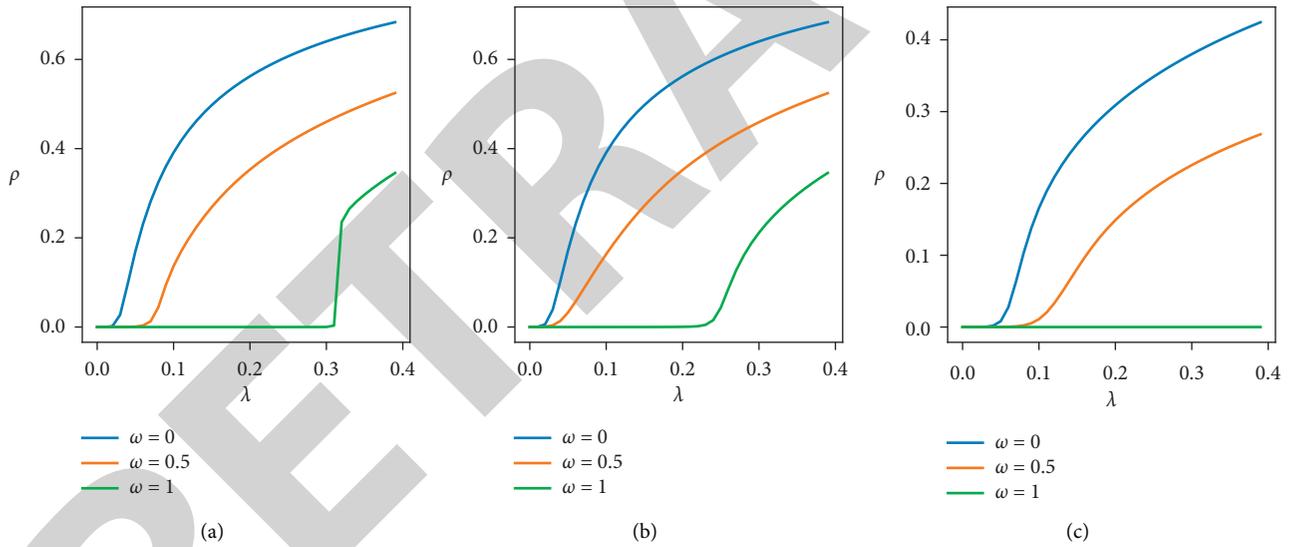


FIGURE 3: Continued.

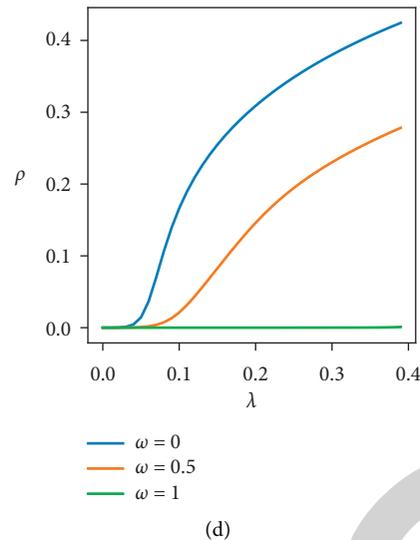


FIGURE 3: Information spreading on activity-driven networks. The final information spreading size ρ versus information transmission probability λ with $\rho_0 = 0.1$ (a) and $\rho_0 = 0.9$ (c) for $\gamma = 2.1$. ρ versus λ with $\rho_0 = 0.1$ (b) and $\rho_0 = 0.9$ (d) for $\gamma = 3.5$. We set $\xi = 0.5$ and $\langle k_t \rangle = 10$.

5. Conclusions

In this paper, we proposed a mathematical model to investigate the effects of network memory on the information spreading dynamics on temporal networks. We first proposed a dynamical model in which the temporal network has a memory effect. Specifically, the current temporal network can remember the previous interconnections. Furthermore, an information diffusion model is developed on this type of temporal network. Then, we used a Markovian approach to describe the information spreading dynamics. Finally, we used the Monte Carlo simulation method to study the information spreading model numerically and found that network memory may promote and suppress the dynamics. The effects depend on the heterogeneous degree distribution and the fraction of bigots in the populations.

The results presented in this paper may shed some light into investigating the dynamics of information on temporal networks. On the one hand, the Markovian theory may be used to study other dynamics on temporal networks. On the other hand, the memory effect of temporal network should be included when studying other dynamics. Finally, some further studies about memory of temporal network should be investigated, for instance, developing more accurate theory and designing more realistic models to describe the spreading dynamics.

Data Availability

The datasets used in the present study are available from the first author upon reasonable request (googlezlf@163.com).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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