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Instantaneous success and influence promotion in cyberspace — how do they occur?

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ABSTRACT

The popularity of online social networks has opened a window through which the dynamical evolution of human behaviors in cyberspace may be studied. In cyberspace, individuals interact with each other through online social networks (OSNs) whose structure co-evolves with the dynamical process. A phenomenon in OSNs is "instantaneous" success, where the influence of an individual can be suddenly and greatly promoted after his/her messages have been reposted by influential users in the network. Using data crawled from Weibo in China, we identify two key ingredients contributing to this phenomenon: the fitness of the message and the position that its author occupies in the network. We articulate a five-state model for co-evolution dynamics on OSNs to explain instantaneous success and permanent influence promotion. Our study provides fundamental insights into human behaviors in cyberspace that is playing an increasingly important role in society, economy, and national defense.

1. Introduction

The advances of information technologies have led to an explosion of human activities in cyberspace ranging from communication, social networking and education to finance and marketing. Human behaviors in cyberspace have become an integral part of the modern society, generating new phenomena beyond those encompassed by the traditional social science. To understand such phenomena is of critical importance to exploiting and regulating cyberspace to better the human society. Online social networks (OSNs) such as Twitter, Facebook, Weibo (Chinese version of Twitter), and WeChat are typical media in cyberspace, which have been generating great impacts and are playing an ever increasing role in the modern society. A unique feature of OSNs is co-evolution: the networks themselves are not static but evolve dynamically together with the processes occurring on them. From a point of view of dynamical systems theory, OSNs are thus extraordinarily complex, with co-evolution posing a major obstacle to formulating a universal mathematical theory to understand their dynamical behaviors.

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Table 1
Detailed information about the nine users analyzed. The number of messages published by the focal user in the 16-week time period is denoted by n_m. The average reposting frequency before and after T_0, denoted by R_0 and R_1, are calculated for the 4-week periods $[T_0 - 8, T_0 - 4]$ and $[T_0 + 4, T_0 + 8]$, respectively.

Index	User ID	Nickname	n_m	T_0	R_0	R_1
1	1679704482	Xu Chuang Trunk	78	2016.03.26	12.5	102.235
2	1934960034	Penguin Classic Music	37	2015.08.11	157.875	138.063
3	1562373795	Mo Xi Zi Shi	25	2015.11.22	26.222	39.0
4	1234739511	Ke Lan	268	2015.10.31	96.940	102.0
5	1403630461	Tang Yi	64	2015.08.22	42.643	85.0
6	2865101843	Chess Player Ke Jie	101	2016.03.09	150.714	418.963
7	1916293114	A Hou Hosea	107	2015.09.24	0.571	5.469
8	1463564877	Wan Shui Sister	78	2015.11.24	60.688	115.0
9	1152440821	Han Song Luo	108	2015.10.01	25.571	19.512

Due to the tremendous advances in information technologies, high throughput tools and methodologies have become routinely available. There have been studies in OSNs to understand various phenomena and issues such as human mobility [1–19], human interest dynamics [20], and the correlation between human behaviors in cyberspace and in physical space [21]. Recent years have witnessed a growth of interest in analyzing, understanding, and exploiting OSNs. For example, the functions of an OSN rely on information sharing and spreading with respect to network topology, leading to work on analyzing the topological structures of OSNs [22–26]. Identification of influential users in realizing certain network functions has also been investigated [27–30]. Other issues studied include the diffusion of information [23,31–33], virus marketing [34] and rumor inhibition [35,36]. The purpose of this paper is to study and understand a remarkable phenomenon in OSNs: instantaneous success (see below for its meaning) of individuals. Going beyond the existing literature, we focus on the issue of the individual's route to success in cyberspace and articulate a five-state model to describe, analyze, and predict the fundamental dynamical processes underlying instantaneous success and the related phenomenon of permanent influence promotion.

Success is ubiquitous in the human society. Traditionally, successes are measured by wealth, reputation, prestigious prize winning, etc. Differing from successes in the traditional human society which typically are a result of long term cumulative efforts of an individual or many individuals, successes in OSNs have a unique feature: they can be achieved in relatively short time. For convenience, we use the term "instantaneous success" to describe the phenomenon. Accompanying instantaneous success is the permanent promotion of the individual's social status in the network. In an OSN, a computationally accessible and reasonable metric to characterize success is the individual's influence. Analyzing examples from the Weibo platform, we uncover a route to success in which an individual's influence is significantly promoted in relatively short time. We identify two factors that play an important role in influence promotion: the intrinsic fitness (attractiveness) of the messages posted by an individual and the position that he/she occupies in the network, the latter determining the number of users who may receive his/her messages. These two factors are found to be essential to instantaneous success. We articulate a mathematical model based on mutual user interactions to explain the evolution of individual's success. The model is validated and its predictive power is tested through simulations.

2. Results of OSN data analysis

To illustrate the phenomena of instantaneous success and permanent influence promotion, we take as an example the user known by the nickname "Chess Player Ke Jie", one of the top chess players in the world. He became popular in Weibo after being reposted by several influential users in the OSN. The background of his success in cyberspace is the competition between Google Alpha Go and a Korean chess player Lee Sedol. On March 9, 2016, the first day of the competition, Ke Jie posted a message on Weibo saying ". . ., it (Alpha Go) cannot beat me!" This message was reposted by "the queen of Weibo" (Yao Chen, a famous Chinese actor with more than 79 million followers) with the comment "Young Heroes [thumb]". Then, some other influential individuals with more than 7 million followers and institutional users with more than 22 million followers (e.g., official Weibo account of Finance.com.cn) also reposted the message. Within just a few days, the frequency that Ke Jie's message was reposted increased suddenly to over 35,000.

Fig. 1(a) plots the final reposting frequency R of Ke Jie's each Weibo message with the corresponding publication date, where T_0 marks the day when the message was reposted by influential users (March 9, 2016), as indicated by the vertical dashed line. The value of R is calculated from the whole set of data in the Weibo system. There is an abrupt increase in the reposting frequency at T_0, which then approaches gradually a stable level higher than that before T_0, implying that the reposting by the influential users not only resulted in an explosive reposting activities by the public but also promoted the popularity of the author permanently. To show the stable promotion behavior, we show the average reposting frequencies in two 4-week periods $[T_0 - 8, T_0 - 4]$ and $[T_0 + 4, T_0 + 8]$ (marked by light blue color), as denoted by the two horizontal dashed lines, respectively. The data of the 4-week interval before and after T_0 are discarded to eliminate the transient behavior.

To provide evidence that the phenomenon of instantaneous success illustrated in Fig. 1(a) is not unique to Ke Jie, we analyze the data of nine randomly selected users in the Weibo platform, whose messages had been reposted by the super

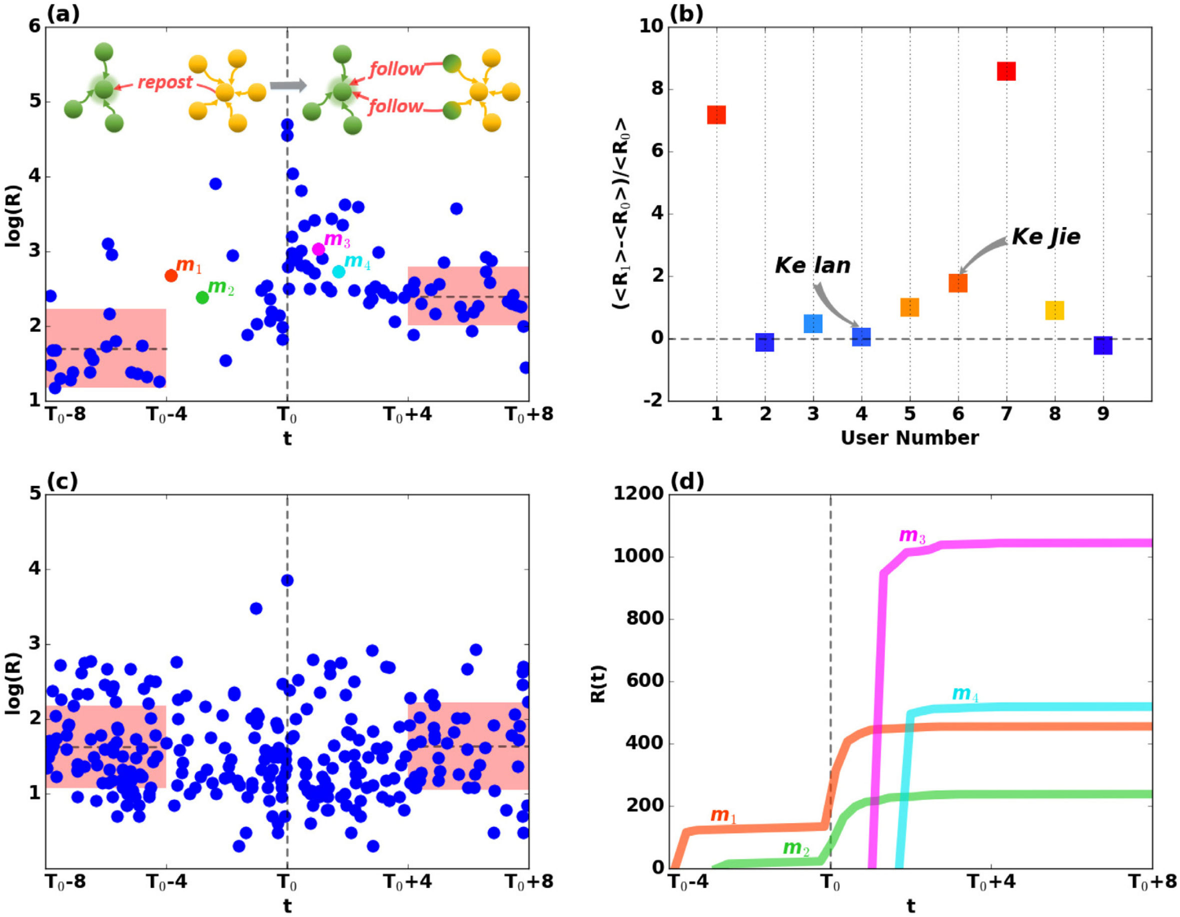

Fig. 1. Analysis of real data crawled from Weibo. (a, c) Reposting frequency of the messages published by user (# 6) during a 16-week time period. The vertical dashed line at T_0 represents the date on which the message of the focal user was reposted by the super hub user. The horizontal dashed lines represent the average reposting frequencies of the messages in the two time periods $[T_0 - 8, T_0 - 4]$ and $[T_0 + 4, T_0 + 8]$, respectively. (b) Relative increment in the average reposting frequency of nine users reposed by Yao Chen. (c) Reposting frequency of the messages published by user # 4, with the same legends as in (a). (d) Temporal behavior of the accumulative reposting frequency of the four messages of Ke Jie marked in (a).

hub node Yao Chen. The detailed information about the nine users is listed in Table 1. For computational feasibility, we carry out a detailed analysis of the data with the nine users to understand the phenomenon of instantaneous success, without resorting to a general statistical analysis that would require significantly more samples. The date each of the nine users was reposted by the super hub is denoted by T_0. For each user, we analyzed records from a 16-week duration of the time interval $[T_0 - 8, T_0 + 8]$. The relative increment in the average reposting frequency after T_0, denoted as $(\langle R_1\rangle - \langle R_0\rangle)/\langle R_0\rangle$, is shown in Fig. 1(b), which is calculated from two four-week periods $[T_0-8, T_0-4]$ and $[T_0+4, T_0+8]$, similar to the case in Fig. 1(a). It can be seen that the distinct increment in the reposting frequency is not necessarily a consequence of reposting by the super hub. Some users (e.g., 1, 5, 6, 7 and 8) experienced a significant increase in the reposting frequency, while some others (e.g., 2, 3, 4 and 9) did not.

For user 4 (Ke Lan, a Chinese actress), whose messages were also reposted by a hub user at T_0, the extent of permanent promotion is not as dramatic as compared with user 6. Fig. 1(c) shows the final reposting numbers R of each message published by user 4 calculated from the whole recorded data. We see that, before the day T_0 reposted by the influential users, the R value is relatively low and stable. With the intervention of the influential user at T_0, the R value associated with the message published for $T = T_0$ increases abruptly and subsequently decays to a stable value. In this case, while there are transient increments in the R value, there is no permanent promotion. We have analyzed the corresponding data and found that the messages that user 4 published in Weibo were mainly associated with personal issues, which were not topics sufficiently appealing to attracting public attention. This example indicates that the contents of the messages depend on the intrinsic characteristics of the user, which can be called as "*fitness*" with respect to the public interest. Whether or not certain messages of a user can be reposted by hub nodes and can lead to a permanent promotion also depends on the fitness of the user.

To uncover the mechanism underlying instantaneous success, we study the temporal behavior of the quantity for user 6. Fig. 1(d) shows the cumulative reposting frequency $R(t)$ of the four messages published by him as a function of time. Typically, the value of $R(t)$ for messages in an OSN tends to reach a limited saturation level far less than the size of the system. For example, the size of Sina Weibo, i.e., the total number of active users, is $N \simeq 2 \times 10^8$, but the highest reposting frequency is about $R = 4.3 \times 10^7$, which was set in June 2015. The bound of the R value can be attributed to reasons such as the sparse connections among the users as compared to those of a fully connected network and user distractions due to other concurrent messages. Fig. 1(d) reveals that the messages published before T_0 (e.g., the two messages indexed as m_1 and m_2), which reached saturation and lost public attention, were reawakened at T_0 and exhibited the temporal behavior of $R(t)$ similar to those of newly published messages.

The mechanism behind message reawakening is different from that of the initial spreading immediately after the publication of the message. The reawakening of certain old messages can be attributed to the new followers of the focal user. Take user 6 as an example. There are two reasons the user to garner new followers after T_0. Firstly, the issues pertinent to "Go" becomes popular because of the game between Alpha Go and Lee Sedol. Secondly, a large number of people were able to review the message published by user 6 due to reposting by a group of highly influential users and became then willing to follow user 6. The new followers may browse previous messages published by user 6 and repost some of them, triggering a reawakening process of the old messages shortly after T_0. Messages m_1 and m_2 demonstrated in Fig. 1(d) are typical examples. In fact, due to the increase in the number of followers, the focal user's network has been extended and served as an updated medium for the spreading of the messages, regardless of whether the messages were old or newly published. A permanent promotion to influence of the focal user has thus been realized through the following process: being reposted by influential users (hub nodes) $\longrightarrow$ collecting new followers to generate a better local network structure for spreading $\longrightarrow$ more followers $\longrightarrow \cdots \longrightarrow$ success – all these can occur in a relatively short period of time.

3. Diffusion model for instantaneous success on OSNs

Our extensive data analysis suggests the following two key ingredients contributing to the phenomenon of instantaneous success on OSNs. The first is the fitness of the messages as determined by other users in the network. In particular, the fitness of a message determines whether other users are interested in reposting the message when they receive it and how likely they may follow the author. The second factor is the position occupied by the author in the network, which determines the number of users who can receive the focal message. Permanent promotion of a user's influence can occur when a large number of new followers respond to the reposting of the message by some influential users, for which both ingredients are necessary. When the fitness value of the author (message) is low, even though the reposting frequency of a single message can be high due to the participation of the influential users, it is unlikely to lead to a sufficient number of new followers to modify the local topology of the original user to induce permanent promotion.

With insights gained from data analysis, we develop a mathematical model based on diffusion dynamics to account for the phenomena of instantaneous success and permanent promotion. There were previous studies on information diffusion in social networks using models from classic epidemiology, such as susceptible–infected–susceptible (SIS) and susceptible–infected–recovered (SIR) models [32,37,38] as well as their variants that were specifically tailored to dealing with information diffusion [23,31,33]. The phenomenon of information explosion on complex networks was also studied [39]. In an epidemic model [31], any individual can be in one of the four states: *Unknown state*, *Known state*, *Approved state*, and *Exhausted state*. Due to the positive role of social reinforcement in information diffusion, the probability for an individual to repost a given message increases with the frequency that the message is received. The existing models are suitable for describing the diffusion of messages on static social networks. To take the time varying nature of OSNs into account, we propose a model with an additional state.

The justifications for our five-state model and the detailed state transitions are described, as follows. An OSN is time varying, as exemplified by the results in Fig. 1. It is the temporal variations of the local network topology which lead to the phenomena of instantaneous success and permanent promotion. In order to take into account the effect of the adjustment in topology, we introduce a fifth state, the "Following state", to describe the users' action to follow those of others. This leads to a five-state model with the distinct states being: "Unknown", "Known", "Approved", "Following" and "Exhausted". The interactions among the five states are necessarily directed. In our model, an OSN is then described by a directed network $G(V, E)$, with the node set V standing for users and the edge set E denoting the relationships among the users. A directed edge from u_b to u_a indicates that u_b is a follower of u_a (the messages posted by u_a can flow to u_b through the edge). Each message has a fitness value. We assume that each node in the network has a fitness value as well, denoted by F_i, which quantifies the attractiveness of all the messages that an individual has posted. From the viewpoint of diffusion of a given message, at any time a user in the network belongs to one of the following five states:

1. *Unknown State*, in which users have not yet been aware of the message;
2. *Known State*, in which users have become aware of the message from the individual they follow but have not reposted it;
3. *Approved State*, in which users have reposted the message to become a spreader so that his/her followers can receive the message from this moment on;

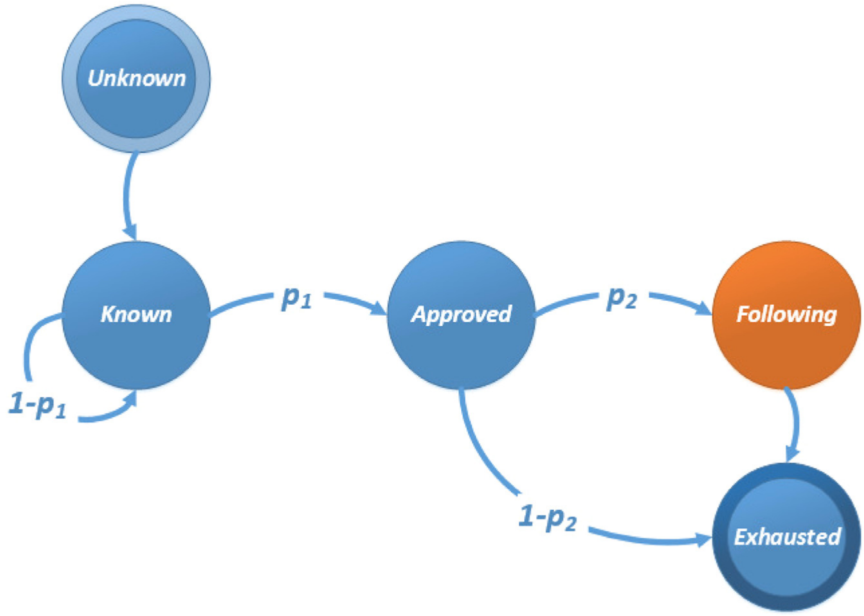

Fig. 2. State transition diagram of five-state diffusion model. See text for details.

4. *Following State*, in which users decide to follow the author after reposting the message, establishing a directed edge from the user in the Following state to the author;
5. *Exhausted State*, in which users become "immune" to the effect of the message after reposting the message and no longer care about whether or not to follow the author of the posted message.

Note that users in the *Exhausted state* do not contribute to the diffusion process. The transitions among the five states are illustrated in Fig. 2.

The dynamical processes taking place in an OSN include the spreading of messages and the simultaneous establishment of follower relationships. To gain insights, we focus on the processes induced by one specific new message initially published by a given seed user in the network, which is conveniently referred to as the author. With respect to the new message, all other users (except the seed user) are in the *Unknown state*. The diffusion of the message occurs iteratively, which can be seen, as follows. During each round, users who receive the information update their states to the *Known state* and then make a decision as to whether or not to repost the message. If yes, the state transitions to the *Approved state*, say with probability p_1. If no, the original state, i.e., the known state, is kept with the probability $1 - p_1$. If a given user has been turned into the approved state, he/she will further make a decision as to whether or not to follow the author. The corresponding probabilities are denoted as p_2 and $1 - p_2$, respectively. That is, with probability p_2 there is a transition to the *Following state* and the probability for the user to remain in the approved state is $1 - p_2$. Any individual who has reposted the message will enable his/her followers to become aware of the message. Those who have already reposted the message or even followed a user will be transferred into the *Exhausted state*. In this model, the probabilities p_1 and p_2 are proportional to the fitness of user F_i. The diffusion process will have been completed when no new user receives any message anymore. As explained, our diffusion model which differs from previous models in our introduction of the *Following state* to capture the co-evolution of the follower networks and the spreading dynamics.

4. Model simulations and results

Our analysis of the Weibo data has identified the fitness F_i of the user and its position in the network as the two determining factors contributing to the popularity of a single message posted by him/her. The user position can be measured by the number of followers and the followers' followers, denoted as ξ_i. Quantitatively, the position ξ_i is approximately the sum of the out-degree of the user: $\xi_i \simeq \sum_{j\in\Pi_i} k_j$, where Π_i is the set of users including i and all the followers, and k_j is the number of followers that user j has. Our simulations aim to reveal the effects of user's fitness, position, and the combination of the two, on the phenomenon of instantaneous success and permanent promotion.

4.1. Effect of user fitness F_i

To be concrete, we assume that the underlying network has the topology of a random regular graph. In this case, the position variable ξ_i is uniform among the users so that the effect of user fitness can be assessed. For instance, we set the

Table 2
Statistics of the graphs used in model simulations, where $G_1(V,E)$ and $G_2(V,E)$ denote random regular graph and a directed heterogeneous network, respectively, k_{in} is the average value of in-degrees, and k_{in} is the average value of out-degrees.

Graph	N_V	N_E	k_{in}	k_{out}	Diameter
$G_1(V,E)$	100	500	5	5	5
$G_2(V,E)$	100	500	5	5	6

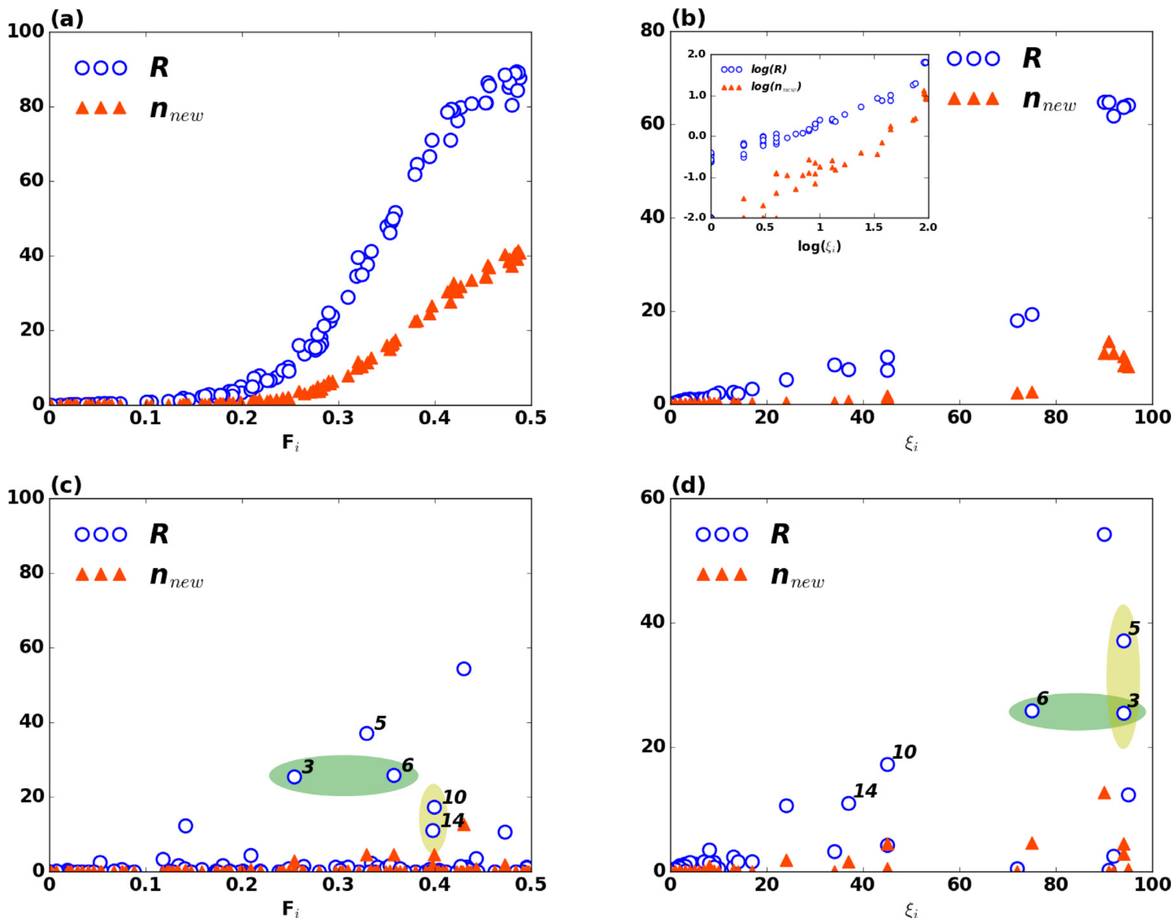

Fig. 3. Representative simulation results of the five-state diffusion model. The average numbers of the users who repost the message and of the new followers that the author acquired due to the diffusion, R and n_{new}, respectively, versus: (a) fitness F_i for random regular networks, (b) the position parameter ξ_i for scale-free networks with a uniform fitness value, (c) F_i for scale-free networks with non-uniform position values, and (d) ξ_i for scale-free networks with non-uniform fitness values.

random regular network composed of 100 users with in- and out-degree to be five, i.e., each user has 5 followers and follows 5 other users. The setting of the random regular network $G_1(V,E)$ is specified in Table 2.

In our simulations, we assign the fitness F_i of author i and his/her message a random value between 0 and 0.5. The probability for the other users to repost the focal message of author i is $p_1 = F_i$, and the probability for the user who has reposted the message to follow author i is $p_2 = F_i$. The spread of the message is terminated when no more reposting and following events take place. For each user, the diffusion process is repeated 100 times. The average numbers of the users who repost the message and of the new followers that the author acquired due to the diffusion are denoted as R and n_{new}, respectively. Fig. 3(a) shows R and n_{new} as a function of F_i for the random regular graph topology, where for each value of F_i, the diffusion process is restarted with the identical original network. We observe a monotonic increase of R and n_{new} with F_i, indicating the positive role of fitness in promoting success.

4.2. Effect of user position

In an OSN, the positions of the users are heterogeneous. We thus adopt the standard scale free network model [40], where one newly added user tends to build up a directed link to a user of larger degree. This scenario is typical in real social networks [41]. The generated directed scale free network has a heterogeneous in-degree distribution. The fitness value is set to be uniform for all the users.

The detailed simulation setting for $G_2(V, E)$ is listed in Table 2. The directed scale free network $G_2(V, E)$ has 100 users, where each user, when being added into the network, follows five existing users. We set $F_i = 0.3$ for all the users. Fig. 3(b) shows R and n_{new} versus the position parameter ξ_i. In spite of small fluctuations, both quantities increase with ξ_i. The trend of increase in turn implies that the parameter ξ_i is appropriate for quantifying the user's position in the message diffusion process. The inset of Fig. 3(b) shows the plots of $\log R$ and $\log n_{\text{new}}$ versus $\log \xi_i$, which are not strictly parallel. This can be attributed to the saturation effect in acquiring followers in a finite size system. In our model, the number of new followers acquired is $n_{\text{new}} = n_{\text{repost}} \cdot p_2$, with n_{repost} being the number of users who have reposted the message. Since it is necessary to take into account the original followers in the set of n_{repost} users, we have

$$n_{\text{new}} = (n_{\text{repost}} - n_{\text{old}}) \cdot p_2, \tag{1}$$

where n_{old} is the number of original followers who have also reposted the focal message. The value of n_{old} is proportional to the number k_{in} of followers as $n_{\text{old}} = k_{\text{in}} \cdot p_1$. For a heterogeneous network of *finite size*, although ξ_i increases with k_{in}, the ratio k_{in}/ξ_i also tends to increase.

4.3. Combined effects of user fitness and position

We use the graph $G_2(V, E)$ in which the user positions are heterogeneous. The fitness parameters for different users are chosen randomly from the interval [0, 0.5]. Figs. 3(c) and 3(d) show R and n_{new} versus F_i and ξ_i, respectively. Taking several typical users (marked by numbers) as examples, we find that users with both high values of F_i and ξ_i tend to take a greater advantage of message diffusion. For instance, users 3 and 5 share the same value of ξ_i but user 5 has a much higher value of F_i. As a result, the values of R and n_{new} for user 5 are higher than those for user 3. Likewise, users 10 and 14 have a similar F_i value but user 10 has a higher ξ_i value, so the latter has higher values of R and n_{new} than those for user 14. In another case, user 3 has a higher ξ_i value than user 6 but the latter has a higher F_i value than the former. As a result of the balance of the effects of fitness and position, the two users have similar R and n_{new} values.

4.4. Permanent promotion of user influence

The five-state model enables us to establish on a solid ground the empirical finding that the influence of a user with high fitness can get permanently promoted after being reposted by influential users. To proceed, we note that the three types of numerical experiments described above provide strong support for our proposition that the extent to which one user can benefit from the diffusion of his/her own message depends both on the fitness and on his/her position in the network. In reality, the probability for a user with a high value of ξ_i to have influential users in his/her own set of followers is high. To demonstrate the phenomenon of permanent promotion, we simulate the cumulative process of typical user behavior in publishing a series of messages. To be concrete, we choose $G_2(V, E)$ as the underlying social network and a user z with five followers as the focal user, who is assumed to post 100 messages successively. Diffusion of each message would result in the recruitment of new followers, thereby modifying the topology of $G_2(V, E)$ in a continuous fashion. The results are shown in Fig. 4, where the value of fitness F_i of user z is set to be 0.1 in simulations (a, b) and 0.3 in simulations (c, d). In addition, we assume that the messages of user z are not reposted by any influential users in simulations (a, c), but in (b, d) the messages are reposted by an influential user. The simulation settings in Figs. 4(a–d) thus represent the combinations of high or low fitness values and participation or absence of influential users. From Fig. 4(a), we see that, with a low F_i value and in the absence of influential users, the reposting number that user z secures is low and stable. For Fig. 4(b) with a low F_i value but with participation of influential users, the number R of reposting events for a single message reposted by the influential user is indeed high, while the influence of user z remains low - a situation similar to the real event shown in Fig. 1(c). For Fig. 1(c) with a higher F_i value but in the absence of any influential user, the value of R is slightly higher, but for the case in Fig. 1(d) with the same F_i value but with the participation of the influential user, user z is significantly promoted, as all the later messages gain higher values of R.

Due to the constant changes in the public interest or fluctuations of the user performance, in reality, the fitness F_i of messages is in fact a time-dependent variable. For a simple one-peak F_i sequence of messages posted by user z [Fig. 4(e)], the simulation results of R is shown in Fig. 4(f), which reproduces the pattern observed from user 6 (a Go player) shown in Fig. 1(a). As a matter of fact, the related topic about Alpha Go has temporally attracted much attention, and it is reasonable to treat the fitness F_i of the go player as a one-peak time variable.

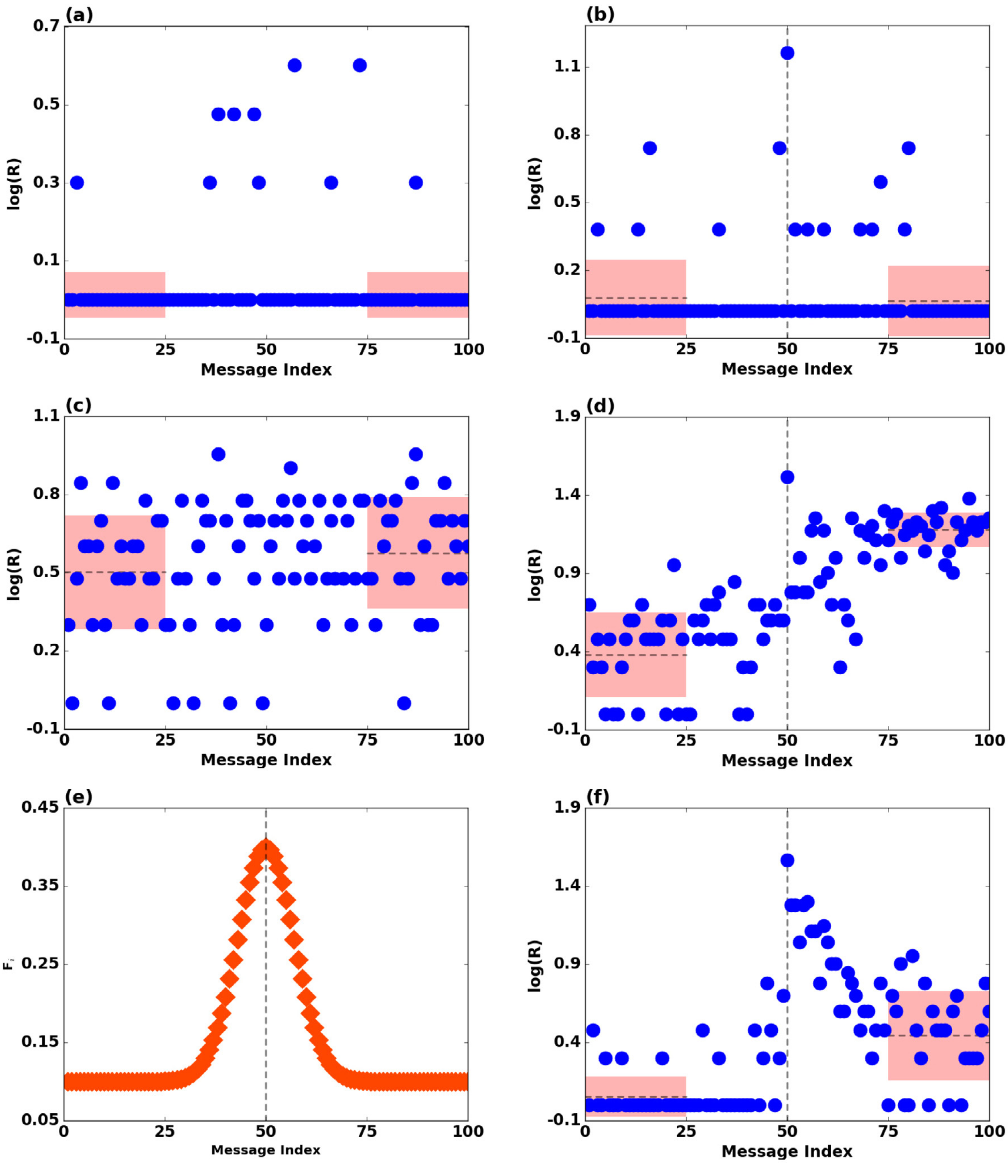

Fig. 4. Diffusion of individual messages on scale-free networks. For a focal user of low fitness ($F_i = 0.1$) posting 100 messages successively, reposting frequency for the messages (a) in the absence of and (b) with the participation of influential users. (c, d) Similar results to those in (a, b) except that the fitness value of the focal user is higher ($F_i = 0.3$). (e, f) A dynamic case where the message fitness is not uniform, where the fitness value for different messages and the corresponding reposting frequencies of the messages are shown, respectively. The vertical dashed lines represent the moment that one message was reposted by influential users and the horizontal dashed lines represent the average values of the reposting frequency, $\log(\bar{R})$, in the corresponding regions of the message index.

4.5. Comparison of degree distribution of model and real Weibo networks

It is useful to compare the degree distribution of a random regular network with that of the real Weibo network, as shown in Fig. 5, where the power law exponent α for the real system is larger than that of the model system, indicating that the stars in the real Weibo system have more chance to attract normal users and to form the star network. These

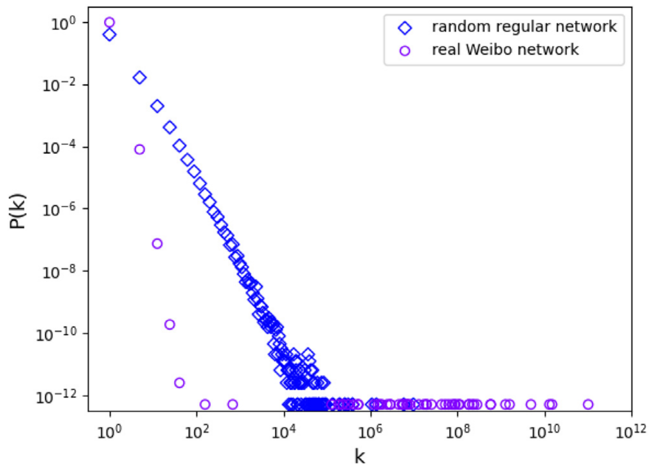

Fig. 5. Degree distribution of user–user retweeting network. The two distributions can be fitted by $P(k) \sim k^{-\alpha}$ with the power law exponent values $\alpha \approx 2.58$ and $\alpha \approx 5.91$ for random regular and the empirical Weibo networks, respectively.

hubs contribute to the long tail of the distribution while the majority of the normal users contribute to the small-degree region, leading to a relatively large value of α. The comparison in Fig. 5 implies that the extreme heterogeneous attraction of users in the Weibo system should be taken into account for further understanding information spreading in the system.

5. Discussion

In cyberspace, there are phenomena that are not usually seen in traditional social networks. One such phenomenon is the instantaneous success and another related phenomenon is permanent promotion of the social status of individuals in OSNs. We have investigated the route to instantaneous success for individuals in cyberspace and found that reposting of an individual's messages by influential users can lead to the permanent promotion of the influence of the individual. From real Weibo data, perhaps the most popular OSNs in China at the present, we have identified the phenomena through examples, such as the instant achievement of fame of a Go player due to reposting by an influential user. As a result, even messages posted by the player that are not directly relevant to the Go game receive significantly more attention than before the reposting by the influential user. These lead to the permanent promotion of the player's general influence in Weibo. The empirical observations suggest a close interplay between the way of diffusion of messages and success, enabling us to articulate a mathematical model for the phenomenon of instantaneous success and subsequent permanent promotion. We have uncovered two key factors underlying the phenomenon: the fitness of the message to general users in the OSN and the position occupied by the author of the message in the network, which has been verified through a series of carefully designed numerical experiments. The dynamical mechanism that the diffusion of one message may bring permanent promotion to the author is that the author acquires new followers during the diffusion process, which changes the topological structure of the underlying network. Empirical results from the real data also suggest the existence of a new dynamical state in the diffusion process, which was not presented in the existing four-state models for OSNs. A key feature of our five-state model is that diffusion leads to the co-evolution of the underlying network. Numerical simulations of the model lead to the phenomenon of instantaneous success and the associated permanent promotion as seen from real data. Especially, the conditions for permanent promotion have been verified as a relatively high fitness of the user and the broadcasting of influential users. The resulting large number of spreaders and new followers change the position (the local topology) of the focal user. Our model thus captures the fundamental feature of OSNs: co-evolution of network structure and diffusion dynamics.

Our work can be viewed as a guide to efficiently and effectively promoting one's influence in OSNs through the exploitation of the attractiveness of the personal messages and a scheme to become more visible through seeking for reposting by influential users. Our work also demonstrates explicitly the "plasticity" of OSNs, i.e., constant modulation of the network structure by the ongoing diffusion process. To our knowledge, prior to our work, there was little effort in modeling the co-evolution of the structure and dynamics of OSNs. Our model treats diffusion of each message of an author as a process of reputation building of the author in cyberspace, and success depends critically on his/her topological position (role) in the network. To gain a more complete understanding of the co-evolution dynamics on OSNs, issues such as social reinforcement effect and development of more accurate measures of the fitness of users and messages must be taken into account, for which further efforts are warranted.

CRediT authorship contribution statement

Ya Chen: Conceptualization, Data curation, Formal analysis. **Xue Li:** Data curation, Formal analysis. **Richong Zhang:** Conceptualization, Methodology. **Zi-Gang Huang:** Conceptualization, Methodology, Writing - review & editing. **Ying-Cheng Lai:** Conceptualization, Methodology, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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