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Competition and Influence Models of Message Transmission in Social Networks

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Abstract. The essay, by means of interdisciplinary research and modeling methods, on base of Message interactive data, analyzes the behavioral habits and characteristics of the individual Message transmission, researches the regularity and characteristics in the process of Message transmission and presents modeling with the individual-based influence model the transmission processes of Message topics which are based on the social networks topology. It studies the interaction between two topics in their transmission by modeling the mutual influence between them. It proclaims the effects on the Message transmission and competition by the factors, such as ways of knowing, occurrence time, public engagement interests, Participation of Message topics, etc. The research in this essay will contribute to the cognition for the basic laws and characteristics of Message transmission and competition in the social networks and has certain theoretical and practical significance for the understanding of human complex group behavior in social networks environment and realistic society and for better analyses for Message user behavior.

Keywords: complex network, information transmission, message network

1 Introduction

The social networks which is composed of Message sending and receiving has become one of the important channels of information transmission, the important means of users' expressing and spreading viewpoints in the social networks and it is often an important site where sudden events produce and form. Therefore, it is necessary to study the structure characteristics of social networks and the Message interaction and transmission characteristics in the network to know and explain the process of Message' formation and transmission, which is of great significance to the security issues of Message transmission, such as grasping the Message trends, guiding the direction of information transmission, building a harmonious social environment etc.

At present, many scholars at home and abroad are studying the complex behavior characteristics of human individual and group in the complex network, the interaction and transmission characteristics of Internet information, the characteristics of information interactive behavior by individuals in the Internet environment and so on, through a large number of real empirical data in Internet, to discover and explain the mechanism generated by human complex behavior in real social networks. The transmission influence model [1-4] has extensive uses in describing lots of transmission processes, such as spread of infectious diseases [5], new products and rumors [6-7], etc., so influence model is very suitable for modeling the information transmission process which is based on certain interpersonal network topology.

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The research for the transmission processes such as the topic transmission formed in blog articles [8-10], the topic transmission of commodity information from the users in commodity evaluation community [11] and the transmission of the pictorial information in the picture sharing community [12-13] etc. has proved, from the empirical point of view, that the influence model based on the user individual interaction can be used for modeling the information transmission processes in the Internet community and is suitable for the description of the information transmission processes in the Internet similar to the probability method of infectious disease transmission [14]. Opinion dynamics aim to understand how social opinions evolve and converge by defining different interaction mechanisms from individual levels [15-16]. Granovetter [17] pointed out that connections in social networks can be divided into strong connections and weak connections, and found that there is a higher clustering phenomenon in strong connected social networks The networks [18] studied by Newman are all small world networks with small average path length and high clustering coefficient, and it is found that network topology, web link structure and neural network have obvious power-law distribution characteristics. In reference [19], the famous Sina blog community is studied, which proves that the interpersonal interaction network formed by Sina blog has the characteristics of small world and power-law distribution. Adamic [20] et al. Studied the interaction data in a community network of Stanford University, and found that this network has the characteristics of a small world model In reference [21-22], a growth model of social networks with power-law characteristics is established to study the law of degree distribution and network decay.

The transmission influence model usually assumes that: individual users may join the transmission of topics under the influence of other neighbor users in human relationship network. And this influence abides by probability method, namely each individual who joins in the transmission will impact its neighbors' joining at a certain probability. Under certain conditions of Internet interpersonal network topology and interaction, some users get the topic information and do first transmission in the network. These initial transmitters will influence other neighbor individuals in network topology to join in the transmission at a certain probability. The assumptions that all the individuals are homogeneous and the influence between all the neighbor individuals is same are fundamentally different from the situation in actual social networks. Because every individual user in the social networks has its own nature and character and the influence of each user on another is various, so it is needed to add the user properties and weight relationships between them in the real social networks to study the interaction processes of Message events and to explore how to guide the topic transmission via Message.

2 Competition and Influence Models of Message Transmission

This article is modeling Message transmission processes based on social networks structure with the transmission influence model based on probability mode. Its basic assumption is that: individual user may join the Message transmission under the influence of other neighbor users in social networks and this influence abides by probability method, namely every individual who joins the transmission will influence its neighbors to join at a certain probability. So the transmission process of Message topics is as follow: under certain conditions of social networks topology and interaction, a group of users get the Message and do first transmission for the topic in the social networks. These initial transmitters will influence other neighbor individuals to join the transmission in their social networks at a certain probability, and then the information transmission process between individuals begins here. With the development of the user interaction process over time, Message topics may be disappearing gradually and may also always attract the interest of a certain number of users and continue to spread.

Assuming that whether or not a user joins the transmission of Message event e depends on this user's level of interest in the involvement of it and the influence of its neighbor users. Set the individual preferences as α and the influence of neighbor users as 1-α. Then the probability that a participant i joins the Message event e at moment t is as following:

$$P_{i,t,e} = \alpha \bullet Attraction_{i,t,e} + (1-\alpha) \bullet Neighbor_{t-1,e} \quad \textbf{(1)}$$

This model similarly assumes that this attenuation of events only acts on individual preferences rather than on neighbors' influence and also this attenuation is in exponential form. The attenuation parameter is: Decay. In addition, the initial seduction coefficient of event e is $Attraction_{i,e}$. Following is got consequently:

$$P_{i,t,e} = \alpha \bullet Attraction_{i,e} \bullet Decay_{i,e}{}^{t} + (1-\alpha) \bullet Neighbor_{t-1,e} \quad \textbf{(2)}$$

The initial seduction describes the levels of interest in people's involving in events' transmission when they initially learn the Message events. The attenuation coefficient describes the trends of people's participation will over time. There is no definite relationship between them. The events with high initial seduction do not necessarily have big interest attenuation coefficient.

The initial seduction is associated with the types of users. For the initial seduction of users who are in the habit of mass texting is bound to be relatively high, so this article is still introducing the three types of users β existing in the real social networks in previous chapter: users who are used to conducting mass texting or forwarding Message, users who forward part of Message received, users who are not fond of mass texting or Message forwarding. The initial seductions of the three types of users are respectively a, b, c.

The influence of neighbor individuals adopts scale models which assume that each individual participating in the Message transmission is likely to influence its neighbors to join the transmission. Set the collection of neighbor individuals for event e transmission in which the individual i joins at moment t-1 as $\Phi_{i,t-1,e}$, set the probability that the individual i is influenced to join the transmission by any neighbor j in it as $Influence_{j \to i,e}$, so the probability that the individual i joins in the transmission under its neighbor's influence at moment t is like this:

$$Neighbor_{nei,t-1,e} = 1 - \prod_{k \in \Phi_{i,t-1,e}} (1 - Influence_{k \to i,e}) \quad \textbf{(3)}$$

Put (3) into (2), get:

$$P_{i,t,e} = \alpha \bullet Attraction_{i,e} \bullet Decay_{i,e}{}^{t} + (1-\alpha) \bullet (1 - \prod_{k \in \Phi_{i,t-1,e}} (1 - Influence_{k \to i,e})) \quad \textbf{(4)}$$

In order to facilitate analysis, we simplify the model parameters as follows: on individual preferences, assuming that the attenuation coefficient of Message events is only related to the event itself with no individual differences and that the initial seduction of Message events is related to the types of Message which users send and receive;

On neighbor influence, considering that in actual social networks, it is for sure that the mutual influence between the individuals who have good relationship with each other is big, so set $Influence_{j \to i,e}$ = j as the degree/the biggest one in network and assume that the weight for individual preferences is α, 1/2. Consequently we get simplified model as the following:

$$P_{i,t,e} = \frac{1}{2} \bullet Attraction_{e}^{\beta} \bullet Decay_{e}{}^{t} + \frac{1}{2} \bullet (1 - \prod_{k \in \Phi_{i,t-1,e}} (1 - Influence_{k \to i})) \quad \textbf{(5)}$$

This model adopting the internal Message data of some group builds a real social networks and clusters the users according to their actual situation in social networks. The percentage of the first category users who are not fond of forwarding Message is 0.45. The percentage of the second category users who forward Message according to certain conditions is 0.5. And the percentage of the third category users who like forwarding Message is 0.05. The initial seduction of the first category is c = 0.1, of the second category is b = 0.5 and of the third category is a = 0.85. Define the two events that take place before and after respectively as a and b and assuming that the attenuation coefficient of them is Decay = 0.85.

In order to display the simulation results, the essay on the one hand gives the gradual progress of Participation over time and on the other hand, for the maximum which the transmission comes to is also a concern worthy of attention, so it also gives the changes of Max Participation with some system variables. These simulation results are obtained by Monte Carlo method, each time step in which shows that each individual makes one decision on whether to participate in the topic transmission.

3 The Analysis of Simulation Results

3.1 The Interplay between Two Synchronizing Message Events

The Message events are always initiated firstly by some individuals and then spread and diffuse between individuals. The number of their initiators will have important impact on transmission.

Fig. 1 and Fig. 2 show the changes of event a Max Participation with the number of event b initiators when the two events synchronize, in which the initiator numbers of event a are the fixed values, 10 and 50 respectively. As we can see from the Fig, as the number of event b initiators increases, so does its Max Participation, while the Max Participation of event a is on a declining curve.

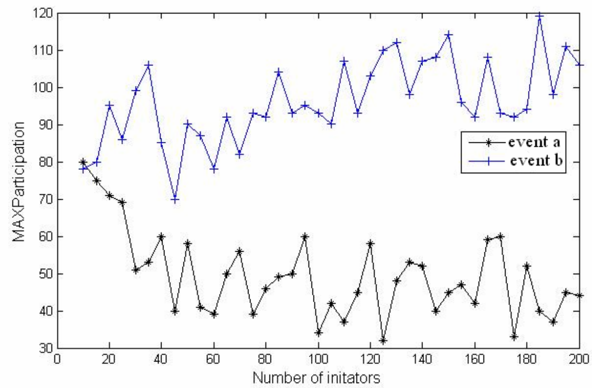

Fig. 1. Shows the variation diagram of the two Message events' Max Participation with event b initiator number when event a initiator number is 10

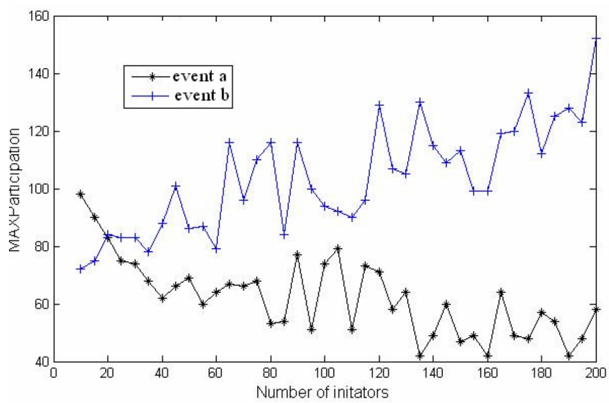

Fig. 2. Shows the variation diagram of the two Message events' Max Participation with event b initiator number when event a initiator number is 50

The number of Message initiators can directly act on the Participation of topics, so the conclusions are drawn as the following: the bigger the Participation of one topic, the stronger its inhibition effect on another topic, which would also make itself more likely to be affected by other topics. This is because the increase of topic Participation will intensify the competition between topics.

3.2 The Effect on Message Transmission with the Increase of Event B Initiators

From Fig. 3 to Fig. 5 show the transmission time curves of the two Message events when they occur at the same time, the initiator number of event a is the fixed value 10 and that of event b takes different values. The dotted line is a reference curve, representing the Participation changes when event a takes place separately:

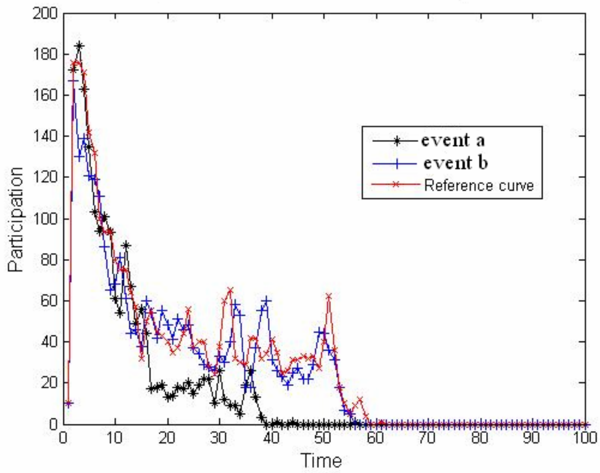

Fig. 3. The variation diagram of the two Message events' Participation over time when event b sponsor number is 10

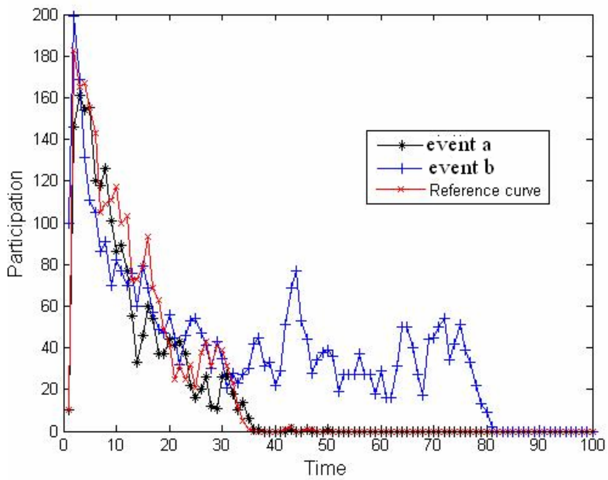

Fig. 4. Variation diagram of the two Message events' Participation over time when event b sponsor number is 40

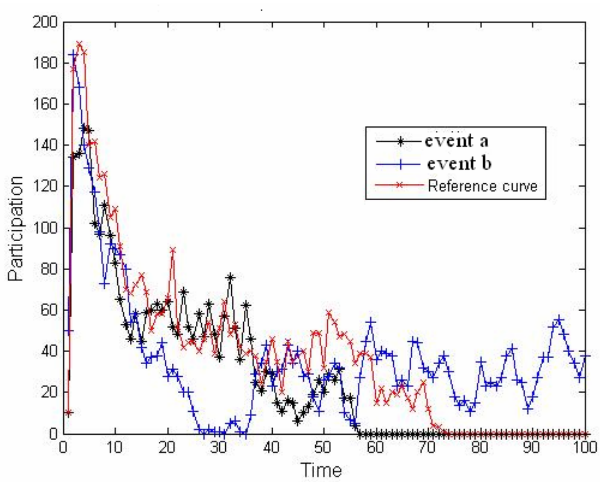

Fig. 5. Variation diagram of the two Message events' Participation over time when event b sponsor number is 100

we can see from the above three Fig, when the initial sponsor number both the two events is 10, the influence of event b on event a is not enormous. But after the number of event b increases to 40 and 100, the Max Participation of event a drops from 190 to 140 and its Participation has been restrained by event b significantly.

3.3 The Effect on Message Transmission of the Types of Initiators of Event B

The interaction between the transmission processes of the Message events has a lot to do with their initiator types. If it is the users of the first category that initially send Message, under whose influence the final Participation must be smallest. If it is the users of the second or the third category that first trigger Message, their influence is bound to increase. Therefore after event a takes place, the influence on it by the initiator types of event b is also an issue deserving research.

The from Fig. 6 to Fig. 8 mainly make simulation analyses of the transmission effects of event b initiator types on event a when the two events synchronize. Both of them have 20 initiators, who of event a are the ones by random and who of event b are successively the ones by random, users of the second category and of the third one.

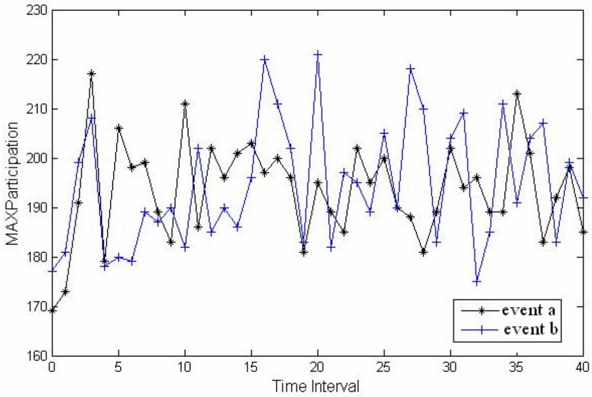

Fig. 6. Shows the influence curve on Max Participation when the initiators of event b are by random.

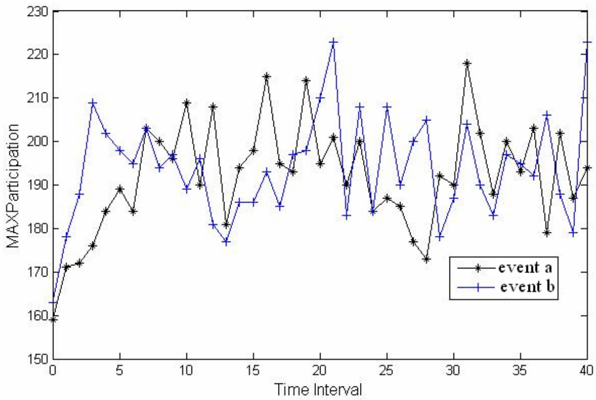

Fig. 7. The influence curve on Max Participation when the initiators of event b are users of the second category

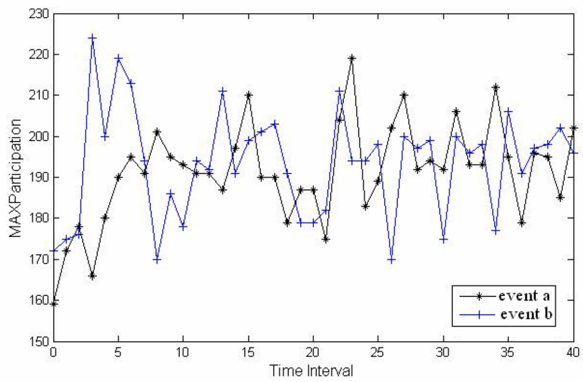

Fig. 8. Shows the influence curve on Max Participation when the initiators of event b are users of the third category

The from Fig. 6 and Fig. 8 show the influence on the Max Participation of the initiator types of event b. As we can see in the above three Fig, the trigger types of event b are of great importance to the interplay between the Message events.

Event b has a best influential point within the time steps from three to seven, within which scope it has the largest impact on event a.

When the initiators of event b are the users of the second or the third category, their influence on event a will be stronger and can preferably suppress its Message transmission.

3.4 Influence on the Time Curve of Transmission Processes with Time Difference

The from Fig. 9 to Fig. 11 describe the curves when two Message events transmit at different time. The initiator number of both event a and b is 20, both of whose types are all by random and event a precedes event b. Hereinto, the dotted line is a reference curve representing the transmission state when event a occurs alone.

As we can see in following Fig, when event b occurs, if event a is close to or through its summit, event b will not much affect its peak value, but will speed up its decline of transmission.

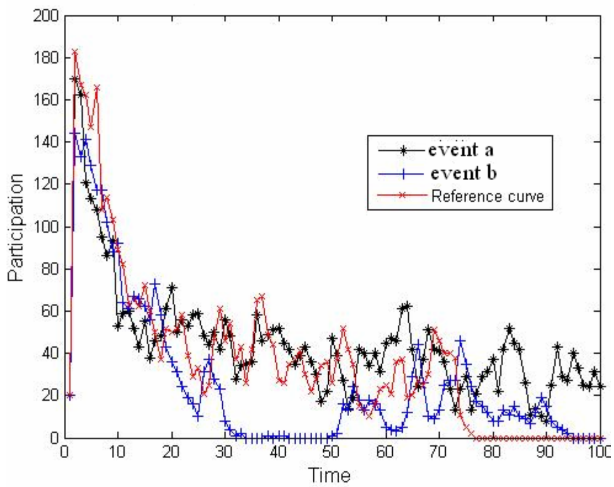

Fig. 9. Shows the variation diagram of two events Participation over time when their time step difference is 0

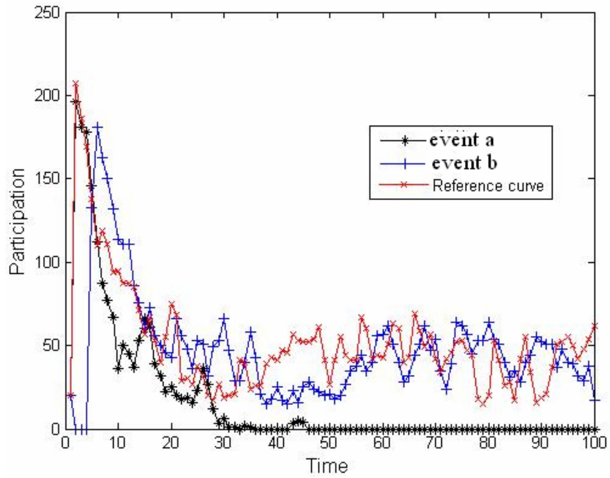

Fig. 10. Shows the variation diagram of two events Participation over time when their time step difference is 5

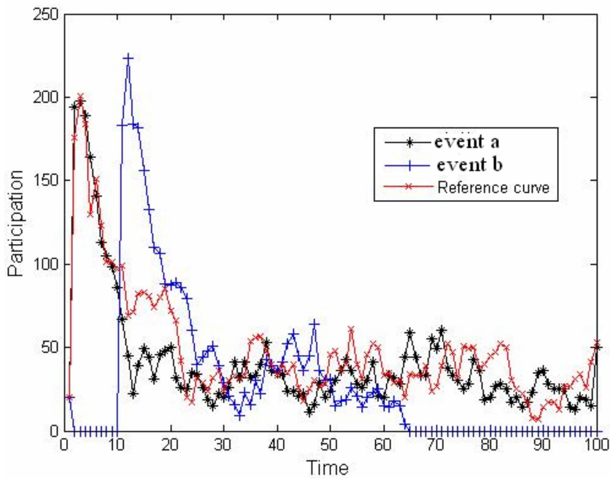

Fig. 11. Shows the variation diagram of two events Participation over time when their time step difference is 10

4 The Effect on Two Message Events Transmission of the Attenuation Coefficient

Attenuation coefficient also has major influence on transmission and competition of topics. Assuming that the two Message events synchronize, initiators of event a are 10 and by random while initiators of event b are 20. The from Fig. 12 to Fig. 14 show the changes of two Message events Max Participation with different attenuation coefficient of event b when the event a parameters remain unchanged. From Fig. 12 to Fig. 14, the initiators of event b are successively by random, users of the second category and of the third one.

The following results can be obtained from the above three Fig:

The attenuation coefficient curve is close to the index. We notice that the attenuation coefficient Decay in formula is in exponential form. Although the formula is the definition of micro individuals' participation strategy, the macroscopic state presented through evolution still shows similar properties with microcosmic.

The changes of Max Participation in the above Fig show that the increase of event b attenuation coefficient will strengthen its competition with event a and minify topic Participation of event a.

The influence on event a by the initial seduction or attenuation coefficient of event b is not linear or in exponential form. The Max Participation curves of event a are more gentle, which means that although adjusting the attenuation coefficient of an event can significantly improve its transmission, the effect of this adjust on the competitive relationships between events is limited. Then the initiators of event b are users of the second and the third categories, they will have greater impact on the Participation of Message event a.

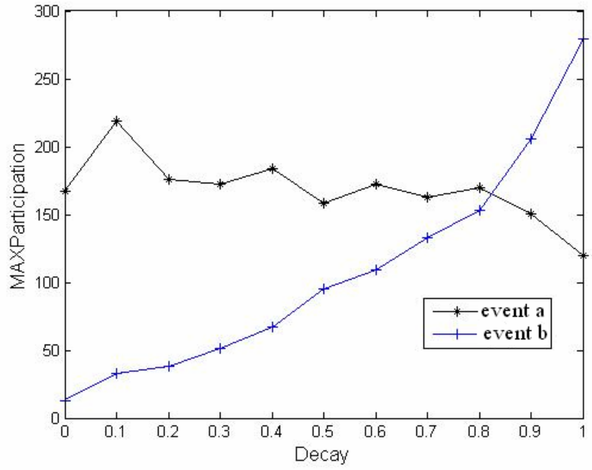

Fig. 12. Shows the curve of Max Participation under the influence of attenuation coefficient when the initiators of event b are by random

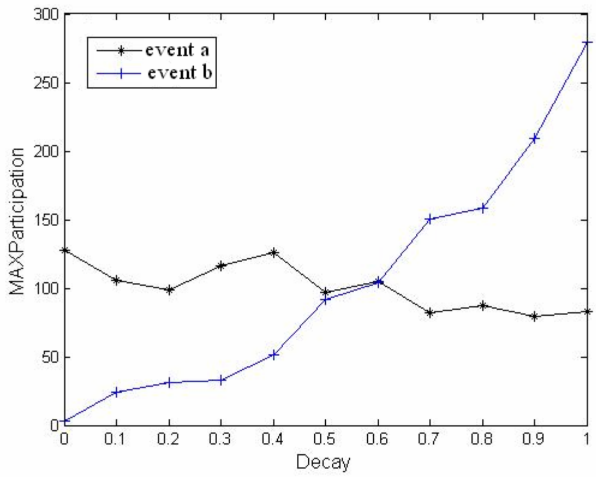

Fig. 13. Shows the curve of Max Participation under the influence of attenuation coefficient when the initiators of event b are users of the second category

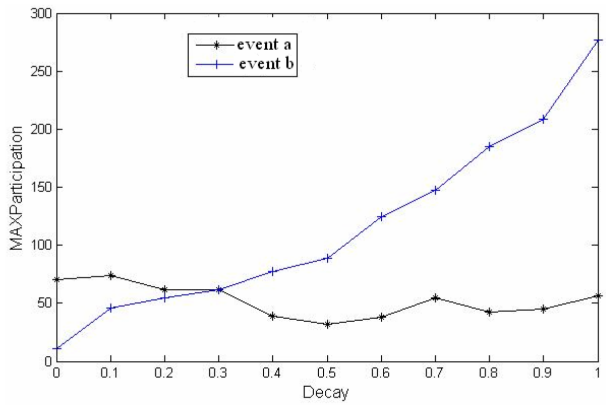

Fig. 14. Shows the curve of Max Participation under the influence of attenuation coefficient when the initiators of event b are users of the third category

5 Summary of This Chapter

This chapter puts forward modeling the transmission processes of topics in fixed Message interpersonal network topology with the theory of influence in probability mode which is based on the individual interactions. When the Participation of Message is of great scale and the time they occur is about the same, there will be mutual influence and competition between their transmission. The essay defines the mutual influence and competition between Message, does simulation study through computer on them and reveals the influence on the transmission and competition of Message with different factors such as Message types, Message occurrence time, Participation and so on. This essay provides a beneficial reference in effectively leading Message transmission.

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