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The Evolving Model of Negative Word-of-Mouth Based On Fuzzy Cellular Automata

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Abstract

Taking the negative word-of-mouth as the content of the study, this paper constructed the evolution model of negative word-of-mouth on the basis of the theory and methodology of Fuzzy Cellular Automata. Simulating experiments is preceded by MATLAB software, and concluded that: The negative publicity causes a surge in the number of negative word-of-mouth initially. If the relevant units or enterprises make a positive response at once, negative word-of-mouth discussion volume will rapid decline and continue to fall; if there is no response, the negative word-of-mouth on volume will keep rising.

Keywords: *Fuzzy Cellular Automata; Negative word-of-mouth; MATLAB; Evolution*

1. Introduction

Information communication between users becomes more frequent and more convenient against the background of widespread use of the network. If the consumer satisfaction of certain product or service is higher, it will naturally win positive word-of-mouth publicity; otherwise, users will complain about it and communicate negative word-of-mouth. Moreover, the anonymity of the Internet enables people to discuss wider, by diverse channels, consumers can spread negative word-of-mouth or even false rumor to more users and influence more people in short run. It is so called "Good news goes on crutches, bad news travels fast". The breadth and depth of internet communication would make the negative news and pejorative commentary of the enterprise and brand which is involved in the scandal blot out the sky [1]. Thus, reputation and sales income of the enterprise would be very difficult to make up. For example, with regard to the influence of botulinum storm, Tencent said in a report: Fonterra imperils dairy, foreign brands didn't sell a tank of milk powder in three days [2].

Word-of-mouth is a collection of consumer opinions, people influence with each other in their opinions. Its formation is a collective phenomenon, and its evolutionary process also shows the complex form [3]. Cellular automata is time, space and variables are all discrete model, because of its wide adaptability, it is considered to be an effective tool for studying complex system [4]. Although the evolution of negative word-of-mouth has a high degree of complexity and uncertainty, not knowing the behavior of all elements in the system, but the system's evolution is from the interaction between person and person, each member adjusts their behavior and state in the next time according to the local information of their neighbors. So this article attempts to use cellular automata to create a negative reputation evolution model and run simulations by using MATLAB software.

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2. Fuzzy Cellular Automata

2.1. Cellular Automata

The Cellular Automata (CA) was introduced in the 1950s by the mathematician John von Neumann [5], and was extended to a broader scientific field by Wolfram in 1986 [6].

Cell, cellular space, neighbor and rules are the most basic elements that make up CA [7]. Simply speaking, CA can be considered as consist of cellular space and the transformation function defined on the space:

$$A = (L_d, S, N, f)$$

where A represents a CA system; L is cellular space; and d is a positive integer, representing the cellular space dimension; S is a finite, and discrete cellular state collection; N represents the combination of all the neighborhood cellular (including the center for cellular), that is a space vector which contains different cellular state; F represents a local transformation function that Sn will be mapped to S ; all cells located in d dimensional space, their location can be determined by a d dimensional integer matrix Z.

The five tuples of CA model is as follows:

(1) Cell: all individual members of a particular space;

(2) Cellular Space: the network space formed by the individual members of organizational structure;

(3) Neighborhood Form: Moore neighborhood with radius 1;

(4) Cellular State Space: Each member's station constitutes the cellular state space.

(5) Rules: a combination of factors changes the cellar's next state according to certain rules.

After the completion of definition of above steps, CA simulation proceeds by updating state variables of each cell through the local switching rules owing to these characteristic [8]. Since CA has been produced, it is widely applied to the field of sociology, biology, ecology, information science, computer science, mathematics, physics, chemistry, geography, environment [9], military science etc. For example, P.Kiran Sree investigated the non-linear classes of CA for predicting heart attack [10]. Pokkuluri Kiran Sree1 and Nedunuri Usha Devi proposed a Linear Cellular Automaton to achieve efficient file compression [11].

In the practical application of CA, due to the incomplete of the complexity of the system and related information, there will be many fuzzy problems [12]. In order to solve this problem better, we can introduce fuzzy theory.

2.2. Fuzzy Inference Theory

Fuzzy logic was first proposed by Zadeh (1965) in the mid-1960s for representing uncertain and imprecise knowledge [13]. The fuzzy controller essentially is a kind of non-linear controller, the fuzzy control algorithms are built up based on intuition and experience about the plant to be controlled [14]. The literature on uncertainty has grown considerably during these last years, especially in the areas of system modeling, optimization, control, and pattern recognition. Recently, several authors have advocated the use of fuzzy set theory to address epidemiology problems [15-17] and population dynamics [18].

The membership function of fuzzy set reflects the degree of subordinate. Its definition is: if any element x of the domain of U , has a corresponding number $\mu_A(x) \in [0,1]$, which gives by degree of membership from x to U . A is called the fuzzy set on the domain U . When x is changing, $A(x)$ is a membership function. $\mu_A(x)$ is closer to 1, saying the high belongs to the degree; the more close to 0, which belongs to the lower level.

Fuzzy rule-based systems will play a key role in this paper, its' framework consists of five parts: input variables, fuzzification, database and rule database, a fuzzy inference machine, defuzzification and output variables.

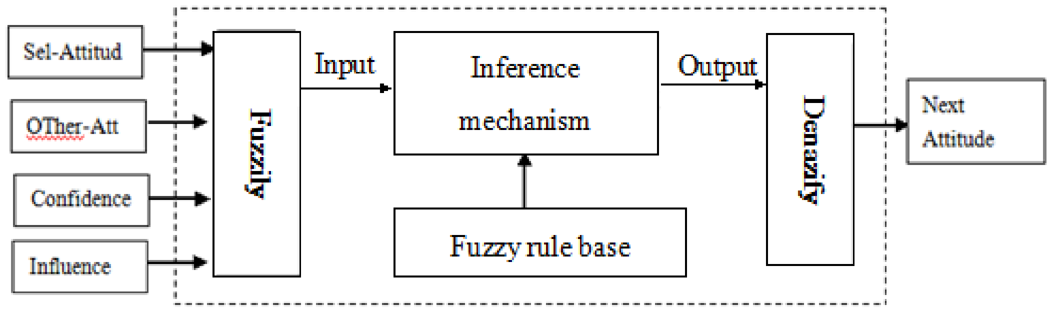

Figure 1. Structure of Fuzzy Rule-based Systems [14]

Fuzzy cellular automata (FCA) is continuous cellular automata where the local rule is defined as the 'fuzzification' of the local rule of a corresponding Boolean cellular automaton in disjunctive normal form [18]. This paper introduces Liu Hongze's (2006) definition of FCA [19]: assuming that L is a well-distributed lattice; S represents the cell's fuzzy state vector; N is a finite set of neighbors (the size is $|N|=n$); r is the neighbor radius; $\hat{f}:\hat{S}^n \to \hat{S}$ is the fuzzy transfer function; to make sure that: $\forall r \in L, \forall c \in N, r+c \in L$.

Fuzzy rules are the key to convert the classical CA for fuzzy cellular automata. We can determine the membership function of the FCA according to the actual problem, and the fuzzy rules can be based on the existing fuzzy theory and the actual situation to establish. Mechanism of FCA is to obtain without precise numerical results through the synthesis of fuzzy set and fuzzy relation, which is in accordance with the given mode of reasoning and rules.

The integrative application of FCA has popularized in many fields and has displayed a wide prospect, such as, geographical information science, environment planning and design, Knowledge-Based System, *etc.*, [19 - 21].

3. Fuzzy Model for Evolution of Negative Word-of-mouth

We can use the fuzzy theory and the theory of CA to simulate the propagation of negative word-of-mouth (WOM), and the inference system is as shown in Figure 2. The input variables are described and explained as follows.

$$f(x) = gaussmf_A(x, \sigma_A, a_A) = \exp[\frac{-(x-a_A)^2}{2\sigma_A^2}] \cdots\cdots\cdots\cdots\cdots\cdots\cdots (1)$$

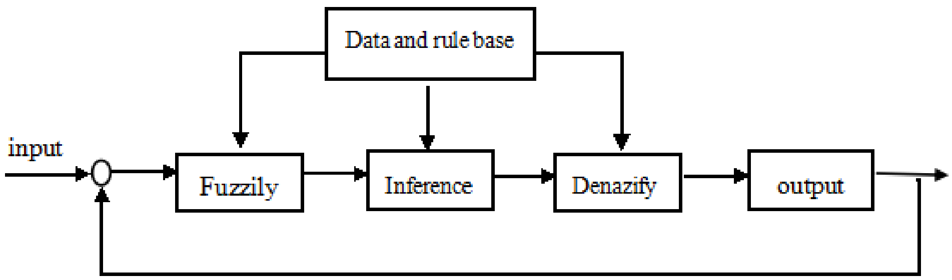

Figure 2. Word-of-mouth Evolution Fuzzy Inference System

3.1. Variables of Negative Word-of-mouth

(1) Cell Attitude: cell attitude is recorded as $A(i, j)$, ranging from [-1,1], fuzzy subset for negative, neutral, positive. Using Gauss function $f(x)$ as the membership function. 1 said cell is in a positive manner, the more closer to the 1, cell attitude is more positive; when -1, said that the cell attitude is negative, closer to the -1 attitude is more negative; 0 said cell neutral. The membership functions of Cell Attitude demonstrated in Figure 3.

a_A and σ_A are the expected value and the standard deviation of the membership function. $\sigma_A = 0.5$, $a_A \in \{-1, 0, 1\}$, and $x \in [-1, 1]$.

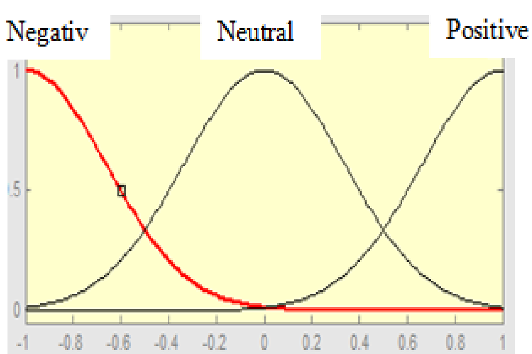

Figure 3. The Membership Function of Cell Attitude

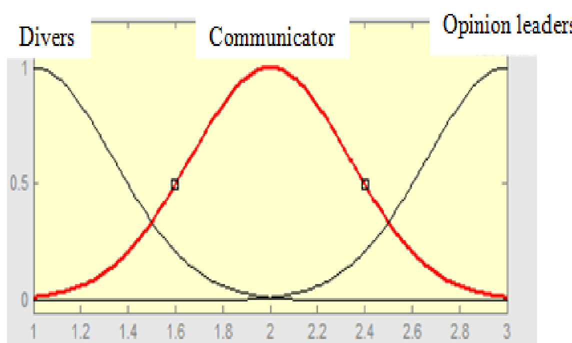

Figure 4. The Membership Function of Cell Type

(2) Cell Types: according to the characteristics of cell to cell is divided into the following three types: Divers, Communicators, Opinion leaders. Using the fuzzy concept to express the cell characteristics, fuzzy membership function to select the Gauss function $g(x)$, ranging from [1, 3].

$$g(x) = gaussmg_A(x, \sigma_A, a_A) = \exp[\frac{-(x-a_A)^2}{2\sigma_A^2}] \cdots\cdots\cdots\cdots\cdots\cdots\cdots (2)$$

a_A and σ_A are the expected value and the standard deviation of the membership function. $\sigma_A = 0.5$, $a_A \in \{1,2,3\}$, and $x \in [1,3]$. A value of 1 indicates cell types for divers, who are not very active community members, they accept the network opinion, but not spread the word; value of 2 said cell type for communicators, who are more active, and will actively participate in the expression of their personal views and opinions to participate in the spread of word-of-mouth; value of 3 represents opinion leaders, who have a certain authority and influence, word-of-mouth is usually spread by opinion leaders.

(3) Cell impact degree: cell attitude is not only affected by the neighbor cell, but also affects the neighbors. Selecting the triangle function as fuzzy membership function, three attributes are high, medium and low, ranging from [0, 1]. The value is closer to 1, the higher the value of influence is, the closer to 0, the lower impact. The membership functions of impact degree demonstrated in Figure 4.

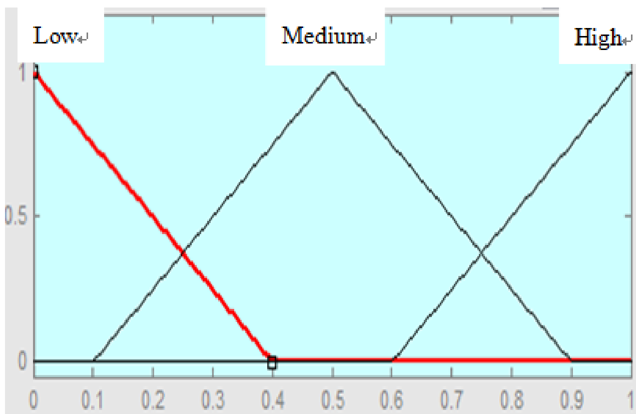

Figure 4. The Membership Function: Cell Impact Degree and Cell Confidence Degree

Cell attitudes and cell types will impact on the cell impact degree. More specifically, negative word-of-mouth has a greater impact; and the effect of opinion leaders is supreme, communicator order, divers hardly effect. So we can construct a fuzzy inference system, input is the cell type and cell attitude, the output is the cell impact degree. The fuzzy rules are listed below.

If (type is Leader) then (impact degree is high);
If (type is Diver) then (impact degree is low);
If (Attitude is Positive) and (type is Diver) then (impact degree is low);
If (Attitude is Positive) and (type is Purveyor) then (impact degree is high);
If (Attitude is Negative) and (type is Purveyor) then (impact degree is high);
If (Attitude is Neutral) and (type is Diver) then (impact degree is low);

(4)Cell confidence degree: each cell has certain persistence on its own attitude, cell confidence degree recorded as $C(i, j)$. Selecting the triangle function $\varphi(x)$ as fuzzy membership function, three fuzzy subsets are high, medium and low, ranging from [0, 1].

$$\varphi(x)=\begin{cases}0 & , x<a_1\\ (x-a_1)/(a_2-a_1) & , a_1\le x<a_2\\ (a_3-x)/(a_3-a_2) & , a_2\le x<a_3\\ 0 & , x\ge a_3\end{cases} \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (3)$$

Here, left point(a_1), central point(a_2) and right point(a_3) determine the shape of membership, |a2−a1| = |a3−a2| = 0.4.

The value of $\varphi(x)$ is more closer to 1, the cell confidence degree is much more higher, the more close to 0, confidence lower. The membership functions of cell confidence demonstrated in Figure 4.

3.2. Negative Word-of-mouth Evolution Fuzzy Rules

Through the above analysis and preparation, electronic word-of-mouth evolution rules can be built. In the initial period, set a few randomly selected cell attitudes value toward -1, to make sure that their attitudes were negative. It can be understood like this: these cells release negative word-of-mouth and influence other cell around them to change attitudes.

Starting from $T=z$, randomly select certain cells, and set their attitudes value to 1, said that the relevant units or enterprises make a positive response and disseminate positive word-of-mouth. In the whole cycle of negative word-of-mouth dissemination, per unit of time, each cell receives the word of mouth information. So, an iterative evolution of FCA is one time unit of information communication in real life.

The next station of the cell is affected by four factors: the cell current attitude, neighbors' attitude, neighbors' influence and the cell confidence degree. Some rules are listed below.

If (Attitude is Negative) and (Nei-Attitude is Negative) then (Next-Attitude is Negative);

If (Attitude is Neuter) and (Nei-Attitude is Negative) then (Next-Attitude is Negative);

If (Attitude is Neuter) and (Nei-Attitude is Neuter) then (Next-Attitude is Neuter);

If (Attitude is Neuter) and (Nei-Attitude is Positive) and (Confidence is high) then (Next-Attitude is Neuter);

If (Attitude is Negative) and (Nei-Attitude is Positive) and (Confidence is low) and (Impact degree is Middle) then (Next-Attitude is Negative);

If (Attitude is Negative) and (Nei-Attitude is Positive) and (Confidence is high) then (Next-Attitude is Negative);

If (Attitude is Positive) and (Nei-Attitude is Negative) and (Confidence is high) and (Impact degree is Middle) then (Next-Attitude is Positive);

If (Attitude is Positive) and (Nei-Attitude is Negative) and (Confidence is Middle) and (Impact degree is high) then (Next-Attitude is Negative);

As a matter of fact, there can be $3*3*3*3$ rules. Otherwise, between some rules there is inclusion relation, or some rules can be reduced. For example, if the cell current attitude is negative, and the neighbor attitude is negative, then no matter how much the confidence and neighbor influence is cell next time still negative attitude. The final 35 rules are not recounted one by one with the limit of space. From Mamdani inference method and defuzzification of the center-of-gravity, the system has obtained the new Attitude of current netizen.

4. Simulation and Analysis

According to the established model, a 50×50 matrix was set for the cellular space. Cell's neighbor form was Moore type neighborhood and the radius was 1. The cell character matrix P, attitude matrix A, confidence degree matrix C was random assignment. And the influence matrix I can be obtained by the sub fuzzy system based on the value of P and A.

4.1. Evolution of Negative Word-of-mouth

In the initial period, set 5 randomly selected cell attitudes value toward -1, to make sure that their attitudes were negative. Starting from $t = 2$, randomly selected several cells, and set their attitudes value to 1. Negative word-of-mouth evolution experiment can be done after setting the parameter values, and then we can show the variations of the negative word-of-mouth quantity in Figure 5.

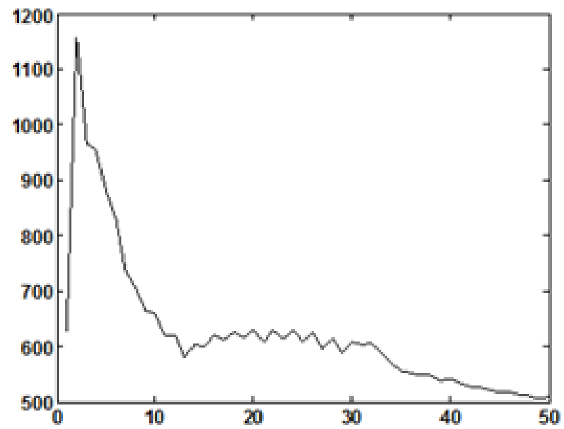

Figure 5. Negative Word-of-mouth Quantity Tendency

Figure 5 shows the process of negative word-of-mouth propagation. Initially, there is a surge in the number of negative word-of-mouth, and it takes a short period of time to peak. If the relevant units or enterprises made a positive response at once, negative word-of-mouth discussion volume would rapid decline and continue to fall.

In order to verify the experiments conclusions, we grabbed 5764 posts date up to 2013-8-31 from iPhone 5 general discussion in Weiwei network [24]. In general, the more actively netizens take part in the information sharing, the more of an impact he can make. So we can say that the hypothesis 'Effect of opinion leaders is supreme, communicator order, divers hardly effect' mentioned in Section 3.1 is true. Most of the posts are about price, configuration information, hardware, system upgrades, and software applications and so on. This kind of posts does not reflect the likes or dislikes emotion, and can be regarded as neutral word-of-mouth. Posts like 'iPhone5 is a frustrating product' which express distinct personal aversion are regarded as negative word-of-mouth; while another kind of posts clearly reflects the praise attitude likes '2012 of ten products: iPhone5 champion' are regarded as positive word-of-mouth. By statistical analyzing the content of all posts, we can know that the number of negative WOM is 676, which is 3 times more than that of positive word-of-mouth. So negative word-of-mouth can attract more attention and spread more widely than positive word-of-mouth. Figure 6 reflects the changing tendency of negative word-of-mouth.

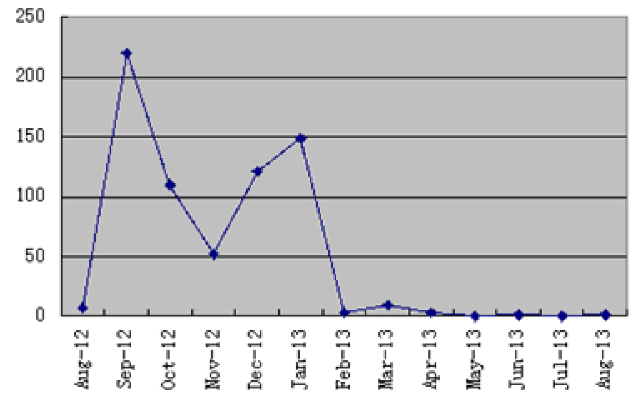

Figure 6. Tendency of Negative Word-of-Mouth

There were 2 peaks in the chart of changing tendency of negative word-of-mouth, this mainly due to the inconsistency between iPhone 5 release date and launch date on the mainland. It can be seen from Figure 3 that negative word-of-mouth quantity reached a peak in a short period of time, and then the discussing volume dropped quickly and continued low volume. This trend confirms the conclusions from Figure 5.

4.2. Effect of Response Time on Word-of-mouth Evolution

In last section, we simulated the evolution of negative word-of-mouth, and raised another question: when is the most appropriate time to intervene the spread of word-of-mouth? Therefore, this section introduces variable q to represent negative (positive) word-of-mouth proportion. Considering that an iterative evolution of CA is one time unit of information communication in real life, so in the experiment we only need to change the value of the intervention time.

When the intervention time is $T = 2$, $T = 5$, $T = 10$, simulation experiments were carried out to get Figure 7- Figure 9, the abscissa represents the iteration number and the ordinate represents negative (positive) word-of-mouth proportion. The followings are respectively on the graphics for the description and analysis.

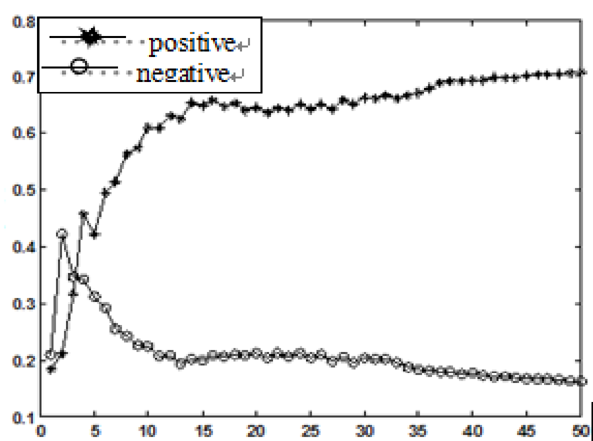

Figure 7. T=2, Changes of the Proportion of WOM

As Figure 7 shows, when the response time was $T = 2$, negative word-of-mouth would be on the rise in a short period of time, but soon began to fall; while the positive word-of-mouth accounted for the overall trend was rising. When reaching the final state, positive word-of-mouth occupied the dominant position, the proportion reached 70%. At this time the brand reputation was positive.

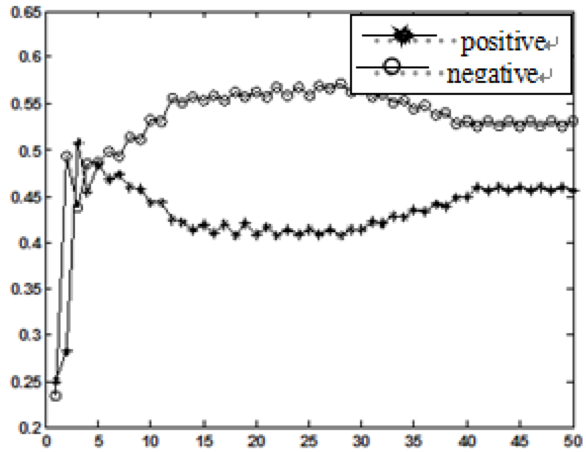

Figure 8. T=5,Changes of the Proportion of WOM

Figure 8 shows that when the response time was $T = 5$, how the proportion of word-of-mouth changed. We could find that the change of positive word-of-mouth and negative word-of-mouth proportion basically was a shift in the state. After reaching steady state, the negative word-of-mouth was slightly higher than the proportion of positive word-of-mouth, but the difference was small, at this time the brand voice gets both praise and blame.

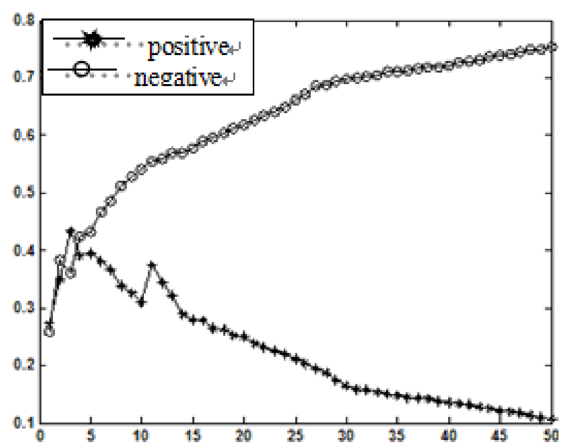

Figure 9. T=10, Changes of the Proportion of WOM

Figure 9 showed that when the response and intervention time was $T = 10$, although in a short time the volume of negative word-of-mouth would rise in volatility, but eventually the negative word-of-mouth occupied the dominant, and the ratio reached more than 70%. Therefore, if the negative word-of-mouth response is not timely, it is likely to cause outbreaks of netizens negative emotions, even result in boycott behavior. For example, in 2012 February the Guizhentang extract bear bile incident, because of its failure to take timely measures to make positive network response, the netizen to boycott Guizhentang volume ratio reached 98%.

5. Conclusion

From this experiment we can conclude that: The negative publicity causes a surge in the number of negative word-of-mouth initially. If the relevant units or enterprises made a positive response at once, negative word-of-mouth discussion volume rapid decline and continued to fall; if there is no response or respond in a way that is not appropriate, the negative word-of-mouth on volume will keep rising.

Therefore, enterprises should immediately respond, or clarify the facts or assume responsibility as soon as the negative electronic word-of-mouth appears on an online bulletin board. If the corporate could guide the media's reporting trend actively, it may become a golden opportunity to build their image and advertise products.

And it would be so worse to hide, escape and shift the responsibility, or force to delete negative electronic word-of-mouth information, or hire network Navy praise yourself, that it can only cause more consumer dissatisfaction, and expand its negative effects. Moreover, negative electronic word-of-mouth information management should not be a short-term burst of activity, it should not be isolated, but should be the normal management combined with other business activities of enterprises. Specifically, the enterprise can invest manpower and material resources to set up relevant departments, establish users' information files, real-time tracking and collecting dynamic information of customers' attitude tendency about products or services.

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