Abstract—Online social networks (OSNs) are becoming an important propagation platform for Word of mouth (WOM). Therefore, it is of great significance to study the propagation of WOM in OSNs. A WOM propagation model named N-P-N is proposed in this paper, and some simulation experiments are carried out to investigate the mechanism of WOM propagation. From the sensitivity analysis of degree of initial information source node, it can be seen that the degree of initial information source node determines the scope and speed of the propagation of WOM in OSNs to some extent. Then the sensitivity analysis of number of initial information source nodes shows that the initial source nodes are crucial for controlling the propagation of negative information in OSNs. Moreover, from the user behavior respect, it is found that different user behavior in OSNs causes different propagation results, the more users who are willing to diffuse WOM, the more scope WOM can propagate and the faster the information diffuses. Findings in this paper are helpful for enterprises to form an effective WOM.

Index Terms—word of mouth, online social networks, information propagation/diffusion

I. INTRODUCTION

Word of mouth (WOM) is the passing of information from person to person by oral communication. In the modern society, WOM is becoming a major information source which can affect current or potential customer's brand choice [1]. WOM is not only conducive to the expansion of businesses, products, brand awareness, more importantly, it can greatly affect the consumers' reputation behavior and attitudes [2]. Katz and Lazarsfeld [3] found that the influence of the WOM among consumers to switch brands is seven times that of the press, four times that of personal selling and two times that of the radio advertising. In the promotion of consumer attitudes from negation, neutral to positive change process, the role of WOM is nine times of advertising.

Since the beginning of the twenty-first century, along with the rapid development of IT and the Internet industry, more and more innovative elements are incorporated into the interactive Internet products. As a new form of network interaction, online social networks (OSNs) with its massive network structure data and user information data, has become a very valuable asset for the study of the WOM. OSNs are also becoming an important propagation platform for WOM, and the information propagation in OSNs is shown in Fig. 1.

II. LITERATURE REVIEW

Dissemination of information refers to a point of view or behavior in the specific structure of the propagation channel is widely spread [7]. This concept has been extensive and in-depth research in the field of epidemiology, sociology and marketing. Biology and epidemiology has conducted in-depth study on diffusion of virus within the group in early time.
[8], and the classical SIS model and SIR model are proposed. In sociology and marketing area, research on diffusion focuses on the problems of innovation diffusion. In the early 20th century, Schumpeter et al. [9] created innovative theory. Then the BASS model [10] opened up new research directions for this research area, and derived a series of related models. Westerman et al. [11] studied the effect of system generated reports of connectedness on credibility, and got that curvilinear effects for number of followers exist, such that having too many or too few connections results in lower judgments of expertise and trustworthiness. Lopez-Pintado et al. [12] studied the product diffusion in complex social networks. He considered the mutual influence among individuals on the micro-level into the propagation equation based on mean-field theory, and found out that innovation diffusion in complex networks also exist a threshold which closely related to the degree distribution and propagation functions of the network. However, Lopez-Pintado only considered the propagation of the positive attitude of the products. In fact, negative attitude about the product will diffuse in the network with the spread of the product and have mutual influence with positive attitude.

Information propagation considering two repellent relationship are studied in the field of competitive marketing and disease control. Dubey et al. [13] studied competitive information game problem in networks based on quasilinear model. They found the Nash equilibrium by considering the adoption of the costs, benefits and external functions of the different information conditions. Bharathi et al. [14] studied competitive information in networks using linear cascade model to compete on the network information. They figured out that the order of information receive time has an important impact on the propagation process of competitive information. Carnes et al. [15] studied the problem of how to selecting the initial users to maximize diffusion influence when a variety of competitive information diffusing in networks. The model considered two kinds of selecting mechanism of competitive information, one is selecting according to the distance between initial information user and individual, another is selecting evenly form the neighbors. Borodin et al. [16] suggested several natural extensions to the well-studied linear threshold model, showing that the original greedy approach cannot be used. Virus propagation and immunization can be considered as two kinds of mutually exclusive information diffusing in networks in the field of disease control. Meier et al. [17] studied inoculation game problem in online social networks, that is, whether each node can select protect itself when virus diffusing in networks. Salathé et al. [18] developed an algorithm that acts only on locally available network information and is able to quickly identify targets for successful immunization intervention, and demonstrated that community structure strongly affects disease dynamics. Budak et al. [19] studied the controlling of negative information in social networks, that is, when negative information is diffused in networks, how to select some nodes to implant positive information in order to correct the information attitude in the whole network to a maximizing extent. They considered positive and negative information propagation contemporary, but ignored the influence of mutual effect between two kinds of information.

III. MODELING THE WOM PROPAGATION

Referred to communicable disease model SIR and SIS [20], a WOM propagation model named N-P-N model is proposed in this section. The basic idea of this model is as follows:

- Different WOM are diffused in OSNs, and users in OSNs are divided into three types based on user behavior:
  - Type A users: WOM cannot affect their attitude of a product or service, and they don’t diffuse WOM information.
  - Type B users: WOM can affect their attitude of a product or service in some extent, but they don’t diffuse WOM information.
  - Type C users: WOM can affect their attitude of a product or service in some extent, and they are willing to diffuse WOM information.
- There are three types of WOM information: positive, negative and neutral. It easier for users to accept the negative WOM than positive WOM. At the initial time \( t=0 \), there are little positive and negative WOM (source node), and along with information propagation, the number of three WOM are changing.
- When \( t=t+1 \), the WOM propagation process is shown in Fig. 2 until the total running time arrives.

As shown in Fig. 2, suppose node \( i \) has WOM attitude \( w_i \), when \( t=t+1 \), the propagation process is defined as follows:

**Step 1**: If \( w_i \) is neutral, the process goes to END. If \( w_i \) is positive, go to Step 2; else if \( w_i \) is negative, go to Step 7.

**Step 2**: If \( i \) is type C, go to Step 3, else go to END.

**Step 3**: Let \( N_i \) represents neighbors of \( i \), then the number of nodes \( n_i \) in \( N_i \) is:

\[
n_i = k_i
\]

(1)

where \( k_i \) is the degree of \( i \).

For each node \( j \in N_i \), go to Step 4.

**Step 4**: If \( j \) is type B or C, go to Step 5, else go to END.

**Step 5**: Suppose node \( j \) has WOM attitude \( w_j \), if \( w_j \) is positive, go to END, else go to Step 6.

**Step 6**: If \( w_j \) is neutral, \( w_j \) will change to positive with the probability of \( p_1 \), and will maintain to neutral with the probability

\[
p_{11} = 1 - p_1
\]

(2)

If \( w_j \) is negative, \( w_j \) will change to positive with the probability of \( p_2 \), and will maintain to negative with the probability

\[
p_{21} = 1 - p_2
\]

(3)

For nodes with negative attitude is more difficult to be changed to positive than nodes with neutral attitude, so the relationship between \( p_1 \) and \( p_2 \) is:

\[
p_1 > p_2
\]

(4)
After the above process, the propagation process goes to END.

Step 7: If \( i \) is type C, go to Step 8, else go to END.

Step 8: For each node \( j \in \{N_i\} \), go to Step 9.

Step 9: If \( j \) is type B or C, go to Step 10, else go to END.

Step 10: If \( w_j \) is negative, go to END, else, go to Step 11.

Step 11: If \( w_j \) is positive, \( w_j \) will change to negative with the probability of \( p_{3j} \), and will maintain to positive with the probability

\[
p_{3j} = 1 - p_{3}
\]

If \( w_j \) is neutral, \( w_j \) will change to negative with the probability of \( p_{4j} \), and will maintain to neutral with the probability

\[
p_{4j} = 1 - p_{4}
\]

For nodes with positive attitude is more difficult to be changed to negative than nodes with neutral attitude, so the relationship between \( p_{3} \) and \( p_{4} \) is:

\[
p_{3} < p_{4}
\]

After the above process, the propagation process goes to END.

Let \( p_A \) represents percentage of type A users; \( p_B \) represents percentage of type B users; \( p_C \) represents percentage of type C users; \( N \) represents the total number of nodes in OSNs. Suppose the number of different nodes at time \( t \) is as shown in Table I. According to mean-field theory [21], after an iteration of the above propagation process, when time = \( t+1 \), the number of each type of nodes is:

\[
n_{ap} = n_{ap} + \frac{n_{an} \times n_{an} \times n_{an} \times n_{an} \times n_{an} \times n_{an} \times n_{an} \times n_{an} \times n_{an} \times n_{an}}{p_{3}}
\]

\[
n_{an} = n_{an} + \frac{n_{an} \times n_{an} \times n_{an} \times n_{an} \times n_{an} \times n_{an} \times n_{an} \times n_{an} \times n_{an} \times n_{an}}{p_{3}}
\]

\[
n_{ane} = n_{ane} + \frac{n_{ane} \times n_{ane} \times n_{ane} \times n_{ane} \times n_{ane} \times n_{ane} \times n_{ane} \times n_{ane} \times n_{ane} \times n_{ane}}{p_{3}}
\]

\[
n_{cp} = n_{cp} + \frac{n_{cp} \times n_{cp} \times n_{cp} \times n_{cp} \times n_{cp} \times n_{cp} \times n_{cp} \times n_{cp} \times n_{cp} \times n_{cp}}{p_{4}}
\]

\[
n_{cn} = n_{cn} + \frac{n_{cn} \times n_{cn} \times n_{cn} \times n_{cn} \times n_{cn} \times n_{cn} \times n_{cn} \times n_{cn} \times n_{cn} \times n_{cn}}{p_{4}}
\]

\[
n_{cne} = n_{cne} + \frac{n_{cne} \times n_{cne} \times n_{cne} \times n_{cne} \times n_{cne} \times n_{cne} \times n_{cne} \times n_{cne} \times n_{cne} \times n_{cne}}{p_{4}}
\]

\[
n_{bp} = n_{bp} + \frac{n_{bp} \times n_{bp} \times n_{bp} \times n_{bp} \times n_{bp} \times n_{bp} \times n_{bp} \times n_{bp} \times n_{bp} \times n_{bp}}{p_{3}}
\]

\[
n_{bn} = n_{bn} + \frac{n_{bn} \times n_{bn} \times n_{bn} \times n_{bn} \times n_{bn} \times n_{bn} \times n_{bn} \times n_{bn} \times n_{bn} \times n_{bn}}{p_{3}}
\]

\[
n_{bne} = n_{bne} + \frac{n_{bne} \times n_{bne} \times n_{bne} \times n_{bne} \times n_{bne} \times n_{bne} \times n_{bne} \times n_{bne} \times n_{bne} \times n_{bne}}{p_{3}}
\]

\[
n_{cp} = n_{cp} + \frac{n_{cp} \times n_{cp} \times n_{cp} \times n_{cp} \times n_{cp} \times n_{cp} \times n_{cp} \times n_{cp} \times n_{cp} \times n_{cp}}{p_{4}}
\]

\[
n_{cn} = n_{cn} + \frac{n_{cn} \times n_{cn} \times n_{cn} \times n_{cn} \times n_{cn} \times n_{cn} \times n_{cn} \times n_{cn} \times n_{cn} \times n_{cn}}{p_{4}}
\]

\[
n_{cne} = n_{cne} + \frac{n_{cne} \times n_{cne} \times n_{cne} \times n_{cne} \times n_{cne} \times n_{cne} \times n_{cne} \times n_{cne} \times n_{cne} \times n_{cne}}{p_{4}}
\]

IV. EXPERIMENTS AND RESULTS

A. Experimental Setup

A randomly generated data set is used for the experiments. There are 2000 nodes in this data set, and the averaged degree is 6. Key features of this data set are summarized in Table II.
The proposed N-P-N model is implemented in Netlogo, which is a simulation software based on agent, on a Microsoft Windows 7 Professional platform with SP1 64 bit edition. The experimental PC is with an Intel Core i7 2620M CPU, 4 GB DDRII 667 MHz RAM, and a Seagate Barracuda 7200.11 500GB hard disk.

<table>
<thead>
<tr>
<th>notation</th>
<th>description</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>number of nodes</td>
<td>2000</td>
</tr>
<tr>
<td>&lt;k&gt;</td>
<td>averaged degree</td>
<td>6</td>
</tr>
<tr>
<td>pA</td>
<td>percentage of type A users</td>
<td>10%</td>
</tr>
<tr>
<td>pB</td>
<td>percentage of type B users</td>
<td>20%</td>
</tr>
<tr>
<td>pC</td>
<td>percentage of type C users</td>
<td>70%</td>
</tr>
<tr>
<td>k</td>
<td>degree of source node</td>
<td>6</td>
</tr>
<tr>
<td>p1</td>
<td>probability of neutral node changed to positive</td>
<td>5%</td>
</tr>
<tr>
<td>p2</td>
<td>probability of negative node changed to positive</td>
<td>0.5%</td>
</tr>
<tr>
<td>p3</td>
<td>probability of positive node changed to negative</td>
<td>1%</td>
</tr>
<tr>
<td>p4</td>
<td>probability of neutral node changed to negative</td>
<td>8%</td>
</tr>
<tr>
<td>n_p</td>
<td>number of initial positive nodes</td>
<td>4</td>
</tr>
<tr>
<td>n_n</td>
<td>number of initial negative nodes</td>
<td>1</td>
</tr>
<tr>
<td>T</td>
<td>total running time</td>
<td>4000</td>
</tr>
</tbody>
</table>

**TABLE II. PARAMETERS SETTING OF DATA SET**

**B. Experimental Results**

First, the running effect of the N-P-N model is given in Fig. 3 and Fig. 4. In Fig. 3, red nodes represent nodes with positive attitude, while green nodes represent nodes with neutral attitude and gray nodes represent nodes with neutral attitude. Fig. 4 shows the percentage change process of the three different nodes.

As shown in the figures, at the initial time (t=0), there are only 4 positive nodes and 1 negative node, while 99.75% of the initial nodes are neutral. As time passed, number of positive nodes rapidly increases. At t=920, the number of positive nodes achieves maximum of 1627. After that, number of positive nodes slowly decreases and finally the number of positive nodes reaches 411. For the number of neutral nodes, it shapely drops to minimum when the model starts running and then maintains an unchanging status.

**C. Sensitivity Analysis of Degree of Initial Information Source Node**

In order to examine how \( k_s \) (degree of initial information source node) affects the propagation of WOM in OSNs, \( k_s \) are changed in the N-P-N model. In the default parameter setting, \( k_s \) is 6, and we change this parameter to 4 and 8 to investigate how it affects the information propagation. The experimental results are shown in Fig. 5.

As shown in Fig. 5, we can see that \( k_s \) determines the scope and speed of the propagation of WOM in OSNs in some extent. Take the neutral nodes for example, when \( k_s \) decreases, the scope of WOM propagation changes a lot (the final number of the neutral nodes is almost two times of that of default setting) while the propagation speed doesn’t change much. The trend of positive and negative nodes is also very different. Take negative nodes for example, when \( k_s \) changes to 8, the maximum number of positive nodes only reaches 30% of that of default setting, while the maximum number of negative nodes is more than that of default setting. Meanwhile, the changing speed is much faster than that of default setting.
D. Sensitivity Analysis of Number of Initial Information Source Nodes

In this section, \( n_{ip} \) (number of initial positive nodes) and \( n_{in} \) (number of initial negative nodes) is changed in order to analysis how different number of initial information source nodes affects the WOM propagation in OSNs. Two more situations are assumed, in which the number of source nodes is gradually increased as shown in Table III.

<table>
<thead>
<tr>
<th>Situation</th>
<th>( n_{ip} )</th>
<th>( n_{in} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Default</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>Situation 1</td>
<td>8</td>
<td>2</td>
</tr>
<tr>
<td>Situation 2</td>
<td>12</td>
<td>3</td>
</tr>
</tbody>
</table>

The running results and the different propagation process are respectively shown in Fig. 6 and Fig. 7.

As shown in Fig. 6, we can see that the number of final negative nodes gradually increases while the number of final positive nodes gradually decreases in situation 1 and situation 2, which illustrates that the more initial source node, the more final negative nodes. Also, we can see in Fig. 7 that the negative information propagation process changes in the three situations. Its changing trend goes steeper and steeper in situation 1 and situation 2 and propagation scope increases while the number of initial source nodes is increasing. However, none obvious rules are found about the propagation process of positive and natural information. These results tell us that the initial source nodes are crucial for controlling the propagation of negative information in OSNs.

E. Analysis of Different User Behavior

In this section, we change the percentage of different user types in order to analysis how different user behavior affects the WOM propagation in OSNs. Two more situations are assumed. In situation 1, we decreases the percentage of Type A and Type B user, and in contrast, in situation 2, the percentage of Type A and Type B user are increased. The parameter setting is shown in Table III.

<table>
<thead>
<tr>
<th>Situation</th>
<th>( P_a )</th>
<th>( P_b )</th>
<th>( P_c )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Default</td>
<td>10%</td>
<td>20%</td>
<td>70%</td>
</tr>
<tr>
<td>Situation 1</td>
<td>0%</td>
<td>10%</td>
<td>90%</td>
</tr>
<tr>
<td>Situation 2</td>
<td>15%</td>
<td>30%</td>
<td>60%</td>
</tr>
</tbody>
</table>

The final running results and the different propagation process are respectively shown in Fig. 8 and Fig. 9.
As shown in Fig. 8, we can see that the final negative nodes are much more in situation 1 than that in default situation and the final neutral node are much more while the final negative nodes are much less in situation 2 than that in default situation. It shows that when $p_C$ (the number of users who want to diffuse WOM in OSNs) increases, the final user with negative attitude will be more. Meanwhile, when $p_C$ decreases, the final user with neutral attitude will be more.

We can see in Fig. 9 that the propagation process changes a lot in the three situations. Its changing trend goes steeper in situation 1 while gentler in situation 2. It shows that when $p_C$ increases, the information spreading speed will be faster, and in contrast, when $p_C$ decreases, the information spreading speed will be slower.

V. SUMMARY
A WOM propagation model named N-P-N is proposed in this paper. From the model, we can investigate some propagation rules of WOM in OSNs. From the sensitivity analysis of degree of initial information source nodes, we can see that the degree of initial information source node determines the scope and speed of the propagation of WOM in OSNs in some extent. Then the sensitivity analysis of number of initial information source nodes tells us that the initial source nodes are crucial for controlling the propagation of negative information in OSNs. Moreover, from the user behavior respect, we find that different user behavior in OSNs causes different propagation results, the more users who are willing to diffuse WOM, the more scope WOM can propagate and the faster the information diffuses. The above results are meaningful for enterprises to form an effective WOM.

REFERENCES


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