A Simulation Approach of Information Propagation in Homogeneous Network

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Abstract. Modelling the behaviour of online social network users’ opinion propagation is of great significance. This paper proposes a method with individual’s own characteristics to model the opinion propagation in homogeneous network. We firstly described the detail of propagation model construction steps including opinion interaction rules, cumulative interaction influence value normalization and historical impact. Then we introduce the definition of individual tolerance to better model propagation. We conducted simulation experiments on two representative propagation networks: ER random network and BA scale-free network. In the end, we give the phenomena and explanation of each simulation result from three aspects.

1. Introduction
Internet public opinion events are aggregation behaviors generated the cognitive cooperative games between individuals on the network. Network individuals express their own demands through network behaviors such as posting, forwarding, and comments, forming the basic situation of network public opinion.

There exist many classic public opinion dynamic models, such as Majority Rule majority model [1], Voter’s voting model [2], H-K limited trust model [3], Sznajd model [4], Deffuant model [5], etc. These models explain some public opinion propagation phenomena by defining simple public opinion interaction rules. However, due to the individual’s own attributes such as different cultural background, education level, mental state, and propensity, it is great different in the discrimination of events between different individuals. The direct reflection is the difference in the expression of emotional attitudes to online public events, and these different expressions are further aggregated into online group behavior to promote the spread, evolution and demise of online public opinion events.

Given the above considerations, this paper proposes a method to introduce the individual’s own characteristics like psychological threshold, i.e., setting for propagation modelling, so as to be able to investigate the impact of different attribute characteristics on the evolution of opinions in a homogeneous network. To better study the characteristics of the evolution of public opinion and the phase transition phenomenon, we conducted experiments on two representative propagation networks: ER random network and BA scale-free network. We adopt the method of synchronous update to analyse the evolution of the model under different network parameters.

The paper is organized as follows. The model construction method is provided in Section 2. The individual tolerance settings are presented in Section 3. In Section 4, the simulation experiments give the results and analysis. The work is summarized and conclusions drawn in Section 5.
2. Model Construction

In a given communication network, individuals express their behavior through forwarding, commenting and replying, forming the interaction and communication of opinions between individuals. At the same time, this kind of opinion interaction between individuals may cause their own opinions to change. We quantified the impact of individual opinion interactions on the individual’s own opinions, and set the individual attribute threshold to construct the model’s opinion interaction dynamics rule, as shown in Table 1.

Table 1. Individual opinion interaction rules.

|                | $Op(-1)$ | $Op(1)$ |
|----------------|----------|---------|
| $Op(-1)$       | $-1$     | $+\alpha$ |
| $Op(1)$        | $-\alpha$ | $+1$   |

In Table 1, the $Op(1)$ and $Op(-1)$ represent two different discrete opinions, positive opinion and negative opinion respectively. When individual $i$ and individual $j$ form an opinion interaction in the network:

- If individual $i$ holds negative opinion $Op(-1)$, while individual $j$ also holds negative opinion $Op(-1)$, this interaction will enhance the negative opinion of individual $i$ by $-1$.
- If individual $i$ holds negative opinion $Op(-1)$, while individual $j$ holds positive opinion $Op(1)$, this interaction will weaken the negative opinion of individual $i$ by $+\alpha$.
- If individual $i$ holds positive opinion $Op(1)$, while individual $j$ holds negative opinion $Op(-1)$, this interaction will weaken the positive opinion of individual $i$ by $-\alpha$.
- If individual $i$ holds positive opinion $Op(1)$, while individual $j$ also holds positive opinion $Op(1) \ Op(-1)$, this interaction will enhance the positive opinion of individual $i$ by $+1$.

According to the interaction rules above, during each round of evolution, the individual of the network interacts with all neighbours around it and obtains a cumulative interaction impact value at this moment. We know that the cumulative interaction impact value for individuals will be extremely different due to the heterogeneity of the nodes in different types of propagation network topologies. In a uniform network, because the average degree between individuals, that is, the average interacting neighbours are approximately the same, the variance of the cumulative interaction impact value of each individual is small. In a non-uniform network, such as a scale-free network, the average degree of each individual is very different, which will lead to a great difference in the interaction influence value of different nodes.

In order to smooth the influence of network heterogeneity on individual interactions in the network, we normalize the cumulative interaction influence value of each individual according to the following formula, so that the interaction influence value of each individual in the network is within the continuous closed interval of $[-1, 1]$.

$$\overline{U_i} = \frac{\sum_{\text{neighbor}(i)} U_q}{\text{Degree}(i)}$$

(1)

According to the above formula, the individual in the network obtains an impact value in $[-1, 1]$ during each round of opinion interaction, and determines the change of individual opinion according to this value.

In addition, we consider that the individual opinions is not only affected by the current interaction influence value, but the historical decision of the individual will also have an impact on the current opinions. Therefore, this paper introduces the parameter $h$ as the influence parameter of individual historical decision-making on the change of current opinions. Then the individual’s opinion value at a
certain moment $t$ is determined by both the current interaction influence value and the influence of historical factors, formulated as:

$$
U^{'}_{\text{Current}(i)} = \overline{U}^{\prime-1}_{\text{Current}(i)} \cdot h + \overline{U}^{'}_{\text{Current}(i)} (1 - h)
$$

(2)

3. Individual Tolerance

We introduce the concept of individual tolerance $\varepsilon$ which means the ability to maintain the individual’s own opinion when an individual interacts with others. The individual tolerance also reflects the individual’s ability to resist the influence of outside opinions. Thus, the change of individual opinion is determined by the final interaction value calculated by formula (2), the individual’s current specific opinion value (positive +1 or negative -1), and the individual’s tolerance, as shown in Figure 1.

![Figure 1. Opinion update diagram with individual tolerance.](image)

When the current specific opinion value held by the individual at the current moment is inconsistent with the interaction impact result calculated by formula (2) during an interaction, if the result exceeds the individual’s tolerance for opinion retention, then the individual will change his opinion, that is, persuaded by his neighbours to express the other opinion. The opinion update rule can be formulated as:

$$
|\overline{U}^{'}_{\text{Current}(i)}| > \varepsilon \quad \&\& \quad op(i) * \overline{U}^{'}_{\text{Current}(i)} < 0
$$

(3)

4. Simulation Experiments

According to the definition of the above model, we construct two types of homogeneous networks using the NetworkX tool [6]: ER random network and BA scale-free network, and adopt the method of synchronous update to analyze the evolution of the model under different network parameters. In the initial state, the node size is set to $N = 3000$, $<k> = 10$, other specific parameters are shown in the figures. During the evolution, we mainly examined two outcome variables: steady-state evolution time ($T$) and final opinion evolution distribution state (%).

We conducted simulation experiments on the following three aspects:

1) We investigated the impact of different network types on ($\%$, $T$). The result is shown in Figure 2.

   The result reveals that the type of network has little effect on the final opinion evolution status. This is because we have made a uniform of the cumulative interaction influence value, and the difference bringing by the degree is smoothed.
2) We investigate the impact of different tolerance values $\varepsilon$ on ($\%$, $T$) under a specific network topology. The result shown in Figure 3 illustrates that the tolerance values have little effect on the evolution of opinion, with just a slight fluctuation.

3) Given a specific propagation network and related network parameters, we examined the influence of the parameter $\alpha$ and parameter $h$ and the distribution of different initial opinions on the model evolution ($\%$, $T$).

Figure 4 shows that the final state of public opinion in the network is mainly determined by the proportion of initial opinions. In addition, firstly, opinions with dominant initial opinions often occupy the final victory, and polarization of opinion distribution occurs. When the initial ratio is less than 0.5, the individual’s cumulative interaction influence value is inversely related to the historical ratio $h$. Considering the more historical value, the opinion evolves towards a balanced direction. The initial opinion will eventually be annihilated with smaller $h$ and larger $\alpha$. Secondly, when the initial opinion ratio is greater than 0.5, $h$ exhibits the opposite effect. At the same time, $\alpha$ and $h$ also exhibit an anti-correlation relationship. When considering too much $h$, no matter how $\alpha$ changes, the network opinion will evolve to the polarized state of the opposite opinion.
Figure 4. Evolution results under different $\alpha$, $h$ and the initial opinion ratio

5. Conclusion
This paper proposes a method to model the opinion propagation in homogeneous network. We firstly described the detail of propagation model construction and then introduce the individual's own individual tolerance, for propagation modelling. To better study the characteristics of the evolution of public opinion and the phase transition phenomenon, we conducted simulation experiments on two representative propagation networks: ER random network and BA scale-free network. Finally, we give the explanation of each simulation result.

The model construction and the definition of individual tolerance are based on homogeneous network. Next, we will further expand this schema to heterogeneous network, so that the model can be used in more scenarios in real world.

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7. References
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