Extending opinion dynamics model for collective online behaviours analysis

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Abstract

In online social networks, opinion dynamics generally lead to different types of collective online behaviour such as consensus, polarization and fragment. Then an open problem arises: how are different typical collective online behaviours emerged from the behavioural decisions of individual and interactions among individuals during the process of opinion dynamics? This work examines the process of opinion dynamic in online social networks and different types of interactions among individuals on this process. An opinion-driven dynamics model, which combines a social network-based opinion dynamics model with generative individual behaviour, is proposed by adding antagonistic responses to the DW model. The proposed model integrates three types of interactions and setting up two thresholds to characterize individual behaviour. The behavioural component utilizes an initiation threshold such that if an individual's opinion exceeds this threshold, the individual will initiate the behaviour. In order to verify the effectiveness of the model, simulations are presented to examine how different typical collective behaviours emerge. As a result, we find that opinion dynamics with different threshold lead to different types of collective online behaviours. The openness of individuals to a differing opinion is the key factors to consensus or fragment.

Keywords: opinion dynamics, consensus, antagonism, fragment, online social network

1 Introduction

Online social networking sites such as Weibo are popular platforms for social interaction which may lead to collective behaviour emerged from local interactions among individuals [1,2]. The interaction can include a broad range of individual decision such as behavioural choices and transitions [3]. Therefore, collective online behaviour is driven by behaviour decisions of individuals in a social network environment, but it is not simply the aggregation of individual behaviours [4-6]. In online social networks, opinion and behaviour are woven into the fabric of individuals' daily life. This naturally leads to opinion and behaviour correlation between connected individuals. Behavioural decisions of individuals are triggered by their opinion and attitudes on a certain topic or events and influenced by the opinion and behaviour of friends or neighbours. Studies have demonstrated that individuals register an immediate and automatic reaction of "good" or "bad" towards everything they encounter in less than a second, even before they are aware of having formed an opinion [7]. Advertising, educational campaigns, and other persuasive media messages are all built on the premise that behaviour follows opinion, and opinion can be influenced with the right message delivered during the process of exchanging [8]. Therefore, there is an unprecedented opportunity to analyze collective online behaviour based on opinion-driven behavioural dynamics model, which assumes that collective online behaviour dynamics combines a social network-based opinion dynamics with generative individual behaviour.

In online environments, there are three typical collective behaviours [9-11]. The first is characterized by the emergence of a global consensus, in which all individuals reach the same state in the long run. Consensus behaviours are driven by opinion agreement and can lead to a movement towards uniformity such as collective condemning. In the consensus behaviours, all individuals have to interact to achieve the same state through changing opinion and behaviour. The second is characterized by the emergency of a bipartite consensus, in which all individuals achieve a double extreme convergence with identical magnitude but opposite sign. Bipartite consensus behaviours are driven by antagonistic opinion and can lead to a polarization phenomenon that often happens in a two-coalition community such that opposite opinions are held by two fractions. The third is characterized by the emergency of a global fragment, in which all individuals hold disagreement in the long run. Fragment is driven by diversity of opinions and lead to an anarchy. In examining three typical collective behaviours, we shall draw heavily on the interactions among individuals and opinions change of individuals. We also need to work on two different levels: the microscopic level, where the

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behavioural decisions of the individual occur, and the macroscopic level where collective behaviour can be observed. The greatest promise lies in analysis of linking microscopic opinion change and behavioural decision to macroscopic behaviours [12,13]. Then two open problems arise: how can we describe the behavioural decisions of individual and analyze different typical collective behaviours emerging from both individual interactions and opinion dynamics? Can we change individuals' opinions threshold to influence the behavioural decisions of individual and collective behaviours?

Analysis of social network-based interactions has proven effective and efficient to the understanding of collective behaviour. Recently opinion dynamics modelling has been provided for the analysis of social influences on individual opinions and the emergency of resulting collective behaviour. Several formal mathematical models have been proposed to simulate opinion dynamic, in which interactions between individuals differ from model to model. However, all opinion dynamic models are built on common theoretical roots, and all individuals adjust opinions based on local rules governing the interaction range, which is so-called neighbour-based method. In these models, a set of individuals are used to populate a community, and are seeded with initial opinion value. Each individual adjusts his opinion in the light of interactions with his neighbours. In order to answer those questions aforementioned, a proper choice of the dynamics modelling is the neighbour-based method. Therefore, an opinion-driven behavioural dynamics model is presented in this paper. In the proposed model, behavioural dynamics combines a neighbour-based opinion dynamics with the generative behavioural decision of individual.

Our purpose in this paper is achieved according to the following three aspects:

(i) As collective online behaviours are driven in part by opinions that individuals hold regarding a certain topic, the opinion-driven mechanism is described by opinion-behaviour mapping based on the interaction among individuals, which is the first step to analyze collective online behaviour.

(ii) As collective online behaviours emerged from individuals' opinions and behaviours which are influenced by their personal social network and updated based on neighbour-based method, an opinion-driven behavioural dynamics model is established to analyze three typical collective online behaviours, namely, consensus, polarization or bipartite consensus and fragmentation.

(iii) This study will examine how individuals' opinion dynamics influence the behavioural decisions of individuals and collective behaviours? Interventions to influence collective online behaviour are presented by applying the proposed model.

The following parts of this paper are organized as follows: In Section 2, we review classical opinion dynamic models and explain why an opinion-driven behavioural dynamics can be used to analyze collective online behavioural. In Section 3, opinion-behaviour mapping is established, and an opinion-driven behavioural dynamics model is presented. In Section 4, the proposed model is applied to analyze collective online behaviours using the method of computer simulating. Finally, the paper is concluded in Section 5.

2 Classical opinion dynamics

Consider that online social network is a graph $G=(V,E)$ with $V=\{1,2,\ldots,n\}$ and $E\subset V\times V$, where a node represents an individual and the edges represent the interactions between two individuals. In the graph, the neighbour set of the vertex i is defined by $N_i=\{\ j\in V \mid (j,\ i)\in E\ \}$.The graph may be directed or undirected. A directed graph is used to model networks where relationships are not symmetric, for example, the follower relationship in Weibo. An undirected graph models a network with symmetric relationships where $(i,\ j)\in E$ implies $(j,\ i)\in E$ such as the friend relationship in Wechat. Two individuals i and j are called adjacent if there is an edge connecting them, i.e., $(i,\ j)\in E$, and individual i is a neighbour of individual j. Although the original work concentrated on mutual exchanges of opinion, interaction relationship in online social network are often regarded as directed edges. In this study, we focus our analysis on directed social networks.

Early works to study opinion dynamics were focused on exploring the patterns of interactions and consensus problem that can explain what kind of interactions will lead to agreement of opinions. There are two classical models including "binary opinions dynamics", where opinions are represented by binary value, and "continuous opinion dynamics", where opinions are represented by real positive numbers. In contrast, the latter deals with the problem of what happens to the probability of choosing one decision over another.

In recent years bounded confidence (BC) models have received significant attention. BC models are genuinely models of continuous opinion dynamics in which individuals have bounded confidence in others opinions. The first version of BC models was developed and investigated by Hegselmann and Krause [14,15], called HK model where agents synchronously update their opinions by averaging all opinions in their confidence bound. The other version was presented by Deffuant and Weisbuch [16,17], called DW model, where a pairwise-sequential updating procedure is employed. Both HK and DW are very similar, and assume that individuals have a continuous opinion and tolerance threshold. The principle of them is that an individual takes into account opinions from others in a limited zone which is defined by the tolerance threshold, around its own opinion. They differ in their update rule. In the DW model agents meet in random pair-wise encounters after which they compromise or not. In the HK model, each agent moves to the average opinion of all agents which lie in his area of confidence.

This study considers the model of group opinion dynamics within an online social network that was DW model. DW model was initially constructed through randomized interactions among individuals who are assigned a random opinion, resided as a value on the interval [0,1] drawn from a uniform distribution and a threshold which limits the number of interactions that will result in an opinion change. The threshold can also be taken as a measure of uncertainty about a given issue, in which the individual opinion moves closer to his neighbours. If the difference between his opinion and that of his neighbours is considered too far apart (that is, exceeds their threshold), he is not willing to receive his neighbours' opinion, and no adjustment takes place. Each individual i has an opinion $x_i(t) \in [0,1]$ in the round t, which is the representation of the individual's support for a certain topic. Let $w_{ij} \geq 0$ be the weight that individual i places on the opinion of individual j with the normalization requirement that $\sum_{j=1}^{n} w_{ij} = 1$. Let $\varepsilon_i \in (0,1)$ be the threshold that represents the effect tolerance of individual i. In each round, each individual adjusts his opinion based on based on opinions of neighbouring agents and their own tolerance, taking a weighted average of his own opinion and the opinions of his neighbours and ignoring neighbours whose opinion is outside individual's tolerance. Collective behaviours take places in the discrete rounds. Specifically, the individual i updates his opinion as follows:

$$x_i(t+1) = w_{i1}x_1(t) + w_{i2}x_2(t) + w_{i3}x_3(t) + \ldots + w_{in}x_n(t), \quad (1)$$

where $w_{ij}>0$ only if $(i, j) \in E$, and $|x_i(t) - x_j(t)| < \varepsilon_i$, otherwise, $w_{ij}=0$.

3 Opinion-driven behavioural dynamics model

3.1 OPINION-BEHAVIOUR MAPPING

Collective online behaviours are emerged from individuals' behaviour decision and interactions among individuals. According to cognitive-behaviour theory, individuals' behaviour decision can be categorized as a behaviour change to the interaction which is triggered by opinion dynamics. In the original definition of DW opinion dynamics, there are two types of potential interactions between two individuals who are neighbours: positive interaction, in which the individuals' opinions and behaviours move closer to one another, and neutral interactions, in which the opinions are considered too far apart so that no adjustment takes place. Although these two possibilities capture a wide range of potential interactions, there is a third possibility in online social network: a negative interaction that drives the opinions of the individuals further apart. The proposed model extends it by adding antagonistic responses in order to enable us to capture a more complete range of interactions between different types of individuals. Besides, we extend opinion dynamics by adding behaviour as illustrated in Figure 1.

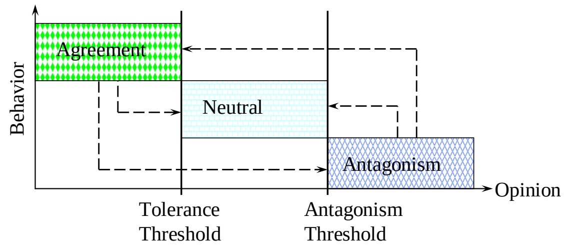

FIGURE 1 Graph illustration of opinion-behaviour mapping in online social network

For purposes of simplicity, a simple step function with the value of the behaviour being either true or false is proposed. The extended model describes the interactions between individuals by postulating that individuals' actions are driven by the objective of maximizing their own expected utilities, which depend on the state of collective behaviours in their own world. Individuals observe the actions of their neighbours, and update their opinions, optimally amalgamating public opinions obtained by observing their neighbours' behaviours. There are two initiation thresholds for every individual, including tolerance threshold and antagonism threshold, especially, the tolerance threshold is less than antagonism threshold. When an individual whose opinion differs from his neighbours by an amount exceeds the antagonism threshold value, he initiates the behaviour to give antagonistic responses to group opinions and collective behaviours. When an individual whose opinion differs from his neighbours by an amount is less than the tolerance threshold value, his opinion and behaviour move closer to group opinions and collective behaviour. When an individual whose opinion differs from his neighbours by an amount is between two thresholds, his opinion and behaviour stay the place. Therefore, addition of antagonistic response and mapping opinions to behaviour to classical DW model enables us to simulate a more complete range of opinion-driven behavioural dynamics among individuals in online social network as follows:

1) Agreement with individuals adjusting new opinions and behaviours closer to their friends whose opinions are similar.
2) Polarization with individuals adopting widely divergent opinions and behaviours when opinion difference exceeds the antagonism threshold.
3) Disagreement with individuals not affected by opinions of their friends where opinion differences are greater than the tolerance threshold.

3.2 THE PROPOSED MODEL

We extend the DW model to directed online social network and interpret the opinion-driven behavioural dynamics to represent overall social influences from all individuals rather than discrete pair-wise interactions. That is, the proposed model considers continuous interactions between individuals rather than the discrete exchanges.

There is a population with N individuals. In the round t each individual i has an opinion $x_i(t) \in[0,1]$ which is the representation of the individual's support for a certain topic, a tolerance threshold determining the latitude of reception $t_i\in(0,1)$ and an antagonism threshold determining the latitude of rejection $a_i\in(0,1)$ with $a_i > t_i$. Let $w_{ij}>0$ be the weight that individual i places on the opinion of individual j with the normalization requirement that $\sum_{j=1}^{n} w_{ij} = 1$. We refer to w_{ij} as the weight of edge (i, j), and $w_i = 1 - \sum_{j\neq i} w_{ij}$. In each round, each individual adjusts his opinion based on based on opinions of neighbouring agents and their own tolerance, taking a weighted average of his own opinion and the opinions of his neighbours and ignoring neighbours whose opinion is outside individual's tolerance. Besides, on account of individuals' different influence in online social network, a parameter is introduced to control for the strength of influence, which is determined by individuals' edges. Collective behaviour takes places in the discrete rounds. More specifically, individual i updates his opinion as follows:

$$x_i(t+1) = w_i x_i(t) + k\sum_{j\in T_i} w_{ij} x_j(t), \quad (2)$$

where T_i is the set of all out-degree neighbours of x_i (t) whose opinions fall out the bounds of antagonism threshold; $w_{ij}>0$ only if $(i, j)\in E$, otherwise, $w_{ij}=0$; k is a coefficient and $k\in\{-1,0,1\}$. If $|x_i(t) - x_j(t)| < t_i$, then $k=1$, and T_i is the set of all neighbours of $x_i(t)$ whose connecting edge points from $x_i(t)$ and whose opinions fall within the tolerance threshold. The process can be viewed as individuals seeking to gain consensus with their friends in online social network. If $|x_i(t)- x_j(t)|\geq a_i$, then $k = -1$, and T_i is the set of all out-degree neighbours of $x_i(t)$ whose opinions fall out the bounds of antagonism threshold. The process can be viewed as some agents seeking to antagonistic response to polarization. If $t_i\leq|x_i(t) - x_j(t)|\leq a_i$, then $k = 0$, $|T_i|=0$ and $w_i =1$.

4 Collective online behaviour analysis

The proposed model is applied to analyze three typical collective behaviours, and explore how three typical collective behaviours are driven by opinion dynamics and what will lead to different collective online behaviours. First we examine how adjusting tolerances influences collective online behaviour, which modify individual tolerances at strategic locations in the network. Next we examine how adjusting antagonisms influences collective online behaviour, which modify individual antagonisms at strategic locations in the network. Finally we examine how adjusting both tolerance and antagonisms influences collective online behaviour, which modify individual antagonisms at strategic locations in the network

According to complex network theory, the ability for a node to influence the network via opinion propagation is primarily determined by an individual's centrality. Online social network members who regularly exchange information with many others in the network are represented by nodes having greater centrality. In online social network, there are some opinion leaders with high centrality, who might have greater influence on making other individuals update opinions toward their own opinion. To effect behavioural change across the network, the proposed model allows us to examine the effectiveness of different nodes importance metric such as the betweenness centrality. Therefore, we adjust the tolerance threshold or the antagonism threshold for the 10 percent nodes with highest betweenness ranking and explore how it influences on collective online behaviour.

We simulated collective online behaviour using the proposed model based on *NetLogo*, which is a programmable modelling environment for simulating natural and social phenomena. The conditions in the simulations are the following: the population N indicates that there are N individuals in online social network, and $[w_{ij}]$ is a $n\times n$ matrix obtained from the adjacent matrix of the network graph. In the experiment, the population is setup N =1000. Every agent has an opinion $x_i(t)\in[0,1]$ at time t and has two thresholds, tolerance T and antagonism A. Given a random network, interactions between two agents have been abstracted as equation (2).

4.1 ADJUST TOLERANCE TO INFLUENCE COLLECTIVE ONLINE BEHAVIOUR

Tolerance in the proposed model indicates the openness of an individual to a differing opinion, and is also termed uncertainty about one's own opinion. In the first experiment, we assume that the tolerance threshold for the ten percent nodes with the highest centrality ranking have the same initial opinion, the same tolerance $T\in(0, 1)$, and a constant antagonism $A = 0.8$. In Figure 2, the diagram shows that adjusting tolerance T results in the emergence of different collective online behaviours in case of the same initial opinion for central nodes. In the second experiment, we assume that the tolerance threshold for the ten percent nodes with the highest centrality ranking have opposite initial opinions, the same tolerance $T\in(0, 1)$ and a constant antagonism $A = 0.8$. One half of the ten percent nodes with the highest centrality ranking have initial opinion $x_i(t)\geq0.9$, the other half of those nodes have initial opinion $x_i(t)\leq0.1$. In Figure 3, the diagram shows that adjusting tolerance T results in the emergence of different collective online behaviours in case of having opposite initial opinion for central nodes.

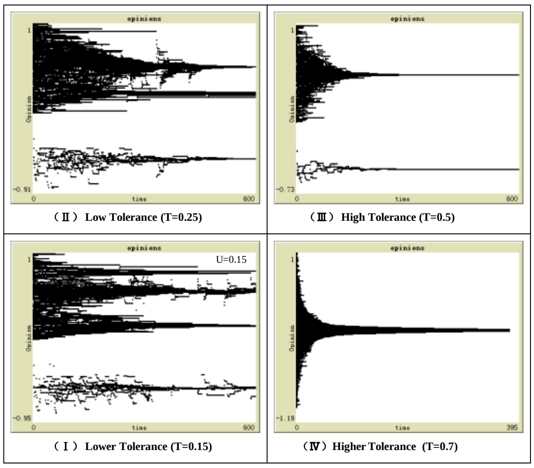

FIGURE 2 The emergency of collective online behaviour in case of different tolerance for central nodes having the same initial opinion and a constant antagonism threshold

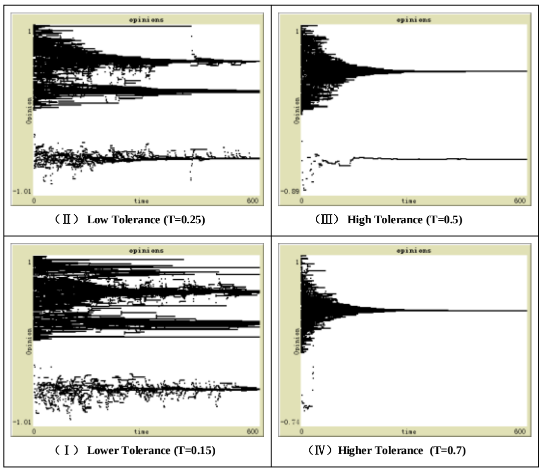

FIGURE 3 The emergency of collective online behaviour in case of different tolerance for central nodes having the opposite initial opinion and a constant antagonism threshold

From the result of simulations, we find that a network composed of individuals with a low tolerance threshold to their neighbours lead to fragment, and a network composed of individuals with a high tolerance typically results in one or bipartite consensus. Our simulations indicate that adjusting the tolerance threshold of the ten percent nodes with the highest centrality can have a dramatic influence on collective online behaviours. Raising the tolerance value of those ten percent nodes above 0.5 resulted in a large increase the possibility of clustering and consensus. Lowering the tolerance value of those 10 percent nodes below 0.5 strongly mitigated the possibility of clustering and consensus, and fragment emerges more easily. Especially, we find that initial opinions of the individuals have no significant impact on collective online behaviour by comparing the results of two experiments. In a word, an online social network composed of nodes with lower tolerance threshold leads to fragment more easily, those networks composed of nodes with lower tolerance threshold result in consensus even if there are three typical interactions including agreement, antagonism and neutrality.

4.2 ADJUST ANTAGONISM TO INFLUENCE COLLECTIVE ONLINE BEHAVIOUR

Antagonism in the proposed model determines the latitude of rejection of an individual to a differing opinion, and is also termed tenacity about one's own opinion. In the third experiment, we assume that the antagonism threshold for the ten percent nodes with the highest centrality ranking have the same initial opinion, the same antagonism $A\in(0,1)$ and $A > T$, and a constant tolerance $T = 0.5$. In Figure 4, the diagram shows that adjusting antagonism A results in the emergence of different collective online behaviours in case of the same initial opinion for central nodes.

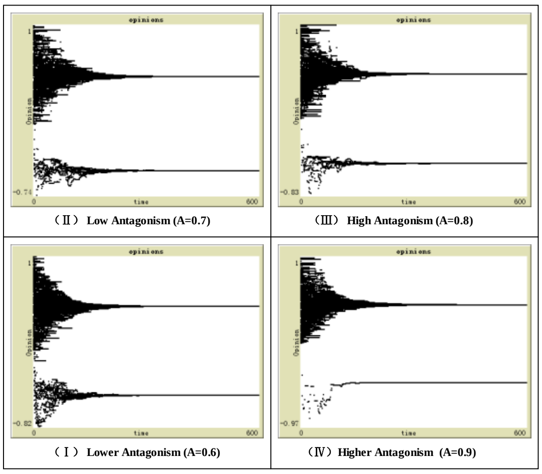

FIGURE 4 The emergency of collective online behaviour in case of different antagonism for central nodes having the same initial opinion and a constant tolerance threshold

In the forth experiment, we assume that the antagonism threshold for the ten percent nodes with the highest centrality ranking have opposite initial opinions, the same antagonism $A\in(0, 1)$, and constant tolerance $T = 0.3$. One half of the ten percent nodes with the highest centrality ranking have initial opinion $x_i(t)\geq 0.9$, the other half of those nodes have initial opinion $x_i(t)\leq 0.1$. In Figure 5, the diagram shows that adjusting antagonism threshold A results in the emergence of different collective online behaviours in case of having opposite initial opinion for central nodes.

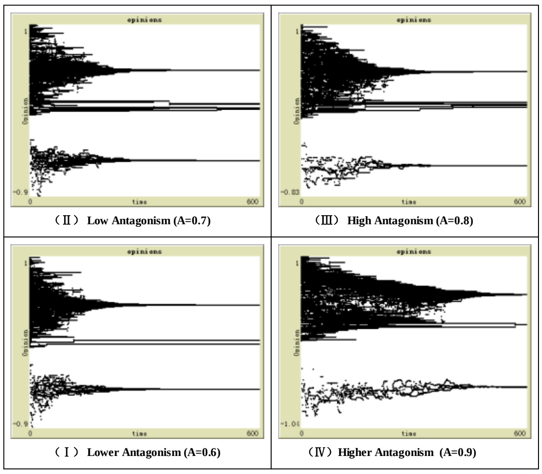

FIGURE 5 The emergency of collective online behaviour in case of different antagonism for central nodes having opposite initial opinion and a constant tolerance threshold

From the result of simulations, we find that a network composed of individuals with both a low and a high antagonism threshold to their neighbours and lead to the same type of collective behaviour, and the difference is only the speed of clustering. A network composed of individuals with a lower antagonism threshold has a higher speed of clustering. Our simulations indicate that adjusting the antagonism threshold of the ten percent nodes with the highest centrality can have a tiny influence on collective online behaviour. With the constant tolerance threshold both raising and lowering the tolerance value of those 10 percent nodes does not change the type of collective online behaviour. Especially, we find that initial opinions of the individuals have no significant impact on collective online behaviour by comparing the results of two experiments.

4.2 ADJUST BOTH TOLERANCE AND ANTAGONISM TO INFLUENCE COLLECTIVE ONLINE BEHAVIOUR

The difference between tolerance and antagonism decides whether an individual takes a neutral interaction with his neighbours. In the last experiment, we assume that individuals are initialized with the same initial opinion, the same antagonism $A\in(0, 1)$ and the same tolerance $T\in(0, 1)$. The values of A and T is varied between 0.1 and the maximum of 1.0 with the constraint of $A > T$.

In Figure 6, the diagram shows that different conditions for the values of T and A result in the emergence of consensus and anarchy. According to the result of simulations, we find that consensus emerges only in case of high uncertainty and high antagonism threshold as (III) shown in Figure 6. In other cases, polarization and fragment emerge as (I), (II) and (IV) shown in Figure 6. Fragment is more notable in case of low uncertainty and high antagonism, while polarization is more notable in case of low antagonism, and bipartite consensus is more notable in case of high uncertainty and low antagonism. As a result, difference between tolerance and antagonism is the key indicator to the emerging of consensus and fragment, and when the difference is smaller, consensus is attained more easily

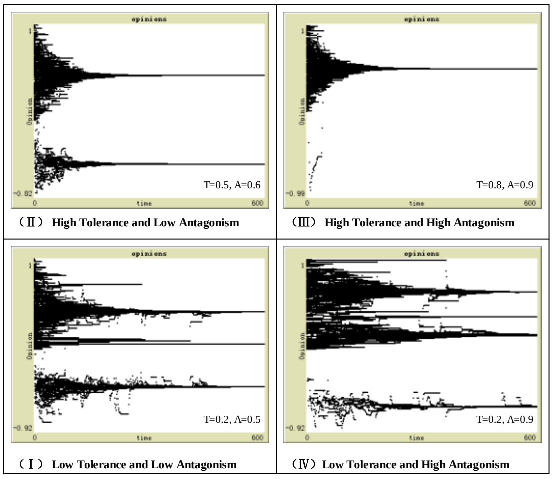

FIGURE 6 The emergency of collective online behaviour in case of a typical opinion trajectory for individuals with different antagonism A and different tolerance threshold T

5 Conclusions

In this paper, we study the process of collective online behaviour triggered by opinion dynamic in online social networks and the influences of different types of interactions among individuals on this process. Our work extended the classical DW model and investigated a possible source of consensus, polarization and fragment by adding antagonistic responses in order to enable us to capture more generative individual behaviours. We consider online social networks as directed graph, and there are three interactions among individuals such as agreement, antagonism and neutrality. The proposed model maps opinion dynamics to collective online behaviour and considers the continuous interactions among individuals. All individuals have a continuous opinion and two thresholds including tolerance and antagonism. We simulated collective online behaviour for the proposed model considered three types of interactions into online social networks based on *NetLogo* to observe the emerging of three typical collective behaviours. As a result, we find that opinion dynamics with different threshold lead to different types of collective online behaviours. The openness of individuals to a differing opinion is the key factors to consensus or fragment. Certainly, our study only focuses on the static social network and simulating for a constructed network. It is a next step to study real and dynamic social networks of collective online behaviour in our future research.

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References

[1] Vispute A, Jadhav P, Kharat P V 2014 Collective Behavior of social Networking Sites *Journal of Computer Engineering* **16**(2) 75-9
[2] Ioanăs E, Stoica I 2013 Social Media and its Impact on Consumers Behavior *International Journal of Economic Practices and Theories* **4**(2) 295-303
[3] Patterson S, Bamieh B 2010 Interaction-driven opinion dynamics in online social networks *Proceedings of the First Workshop on Social Media Analytics* ACM New York NY USA 98-105
[4] Azeem A, Sujata D 2013 Collective behavior of online user based on social media *International Journal of Research in Advent Technology* **1**(5) 572-580.
[5] Bellomo N, Herrero M A, Tosin A 2013 On the dynamics of social conflicts looking for the Black Swan *Kinetic & Related Models* **6**(3) 459-79
[6] Gleesona J P, Cellaia D, Onnelab J P, Porter M A, Reed-Tsochas F 2014 A simple generative model of collective online behaviour *Proceedings of the National Academy of Sciences of the USA* **111**(29) 10411-5
[7] Moore T W, Finley P D, Linebarger J M, Outkin A V, Verzi S J, Brodsky N S, Cannon D C, Zagonel A A, Glass R J 2011 Extending Opinion Dynamics to Model Public Health Problems and Analyze Public Policy Interventions *Proceedings of 29th International Conference of the System Dynamics Society*, Washington DC 1-15
[8] Sobkowicz P, Kaschesky M，Bouchard G 2012 Opinion mining in social media: Modeling, simulating, and forecasting political opinions in the web *Government Information Quarterly* **29**(4) 470-9
[9] Li L, Scaglione A, Swami A, Zhao Q 2013 *IEEE Journal on Selected Areas in Communications* **31**(6) 1072-83
[10] Butail S, Bollt E M, Porfiri M 2013 Analysis and classification of collective behavior using generative modeling and nonlinear manifold learning *Journal of Theoretical Biology* **336** 185-99
[11] Bortolussi L, Hillston J,Latellac D, Massink M 2013 Continuous approximation of collective system behaviour A tutorial *Performance Evaluation* **70**(5) 317-49
[12] Tang L, Wang X F, Liu H 2012 Scalable Learning of Collective Behavior *IEEE Transactions on Knowledge and Data Engineering* **24**(6) 1080-91
[13] Hu J P, Zheng W X 2014 Emergent collective behaviors on coopetition network *Physics Letters A* **378**(26-27) 1787-96
[14] Deffuant G, Neau D, Amblard F, Weisbuch G 2000 Mixing beliefs among interacting agents *Advances in Complex Systems* **3**(1) 87-98
[15] Zhang J B 2014 Convergence analysis for asymmetric Deffuant-Weisbuch model *Kybernetika* **50**(1) 32-45
[16] Hegselmann R, Krause U 2002 Opinion dynamics and bounded confidence: models, analysis and simulation *Journal of Artificial Societies and Social Simulation* **5**(3) 2
[17] Yang Y, Dimarogonas D, Hu X 2014 Opinion consensus of modified Hegselmann-Krause models *Automatica* **50**(2) 622-7

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