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Agent-Based Modelling of Opinion Development in Social Networks: A Social Psychology Approach

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Abstract

The majority of earlier opinion modelling studies did not concurrently examine group dynamics and individual mental processes. The goal of this study is to present an agent-based onlineopinion formation model from the perspectives of sociology and psychology, drawing on group behaviour theory, attitude change theory, and evolutionary game theory. According to this paradigm, the group atmosphere, recipient characteristics, and leaders' trustworthiness all have an impact on the persuasive process. The suggested model is used to examine how opinion leaders, topic type, and parameter changes affect the creation of opinions on Twitter. The results of the experiment demonstrate that there is more sustainability and unpredictability in the opinion evolution of contentious topics.

Opinion formation is greatly influenced by the benefit to cost ratio; the most unified global attitudes or the longest relaxing period will arise from a moderate ratio. In addition, popular opinion might be influenced by celebrities who have a huge following rather than by specialists. The research on opinion formation modelling is enhanced by this work, and the findings offer company managers useful information on public relations and market forecasting.

Keywords

Opinion modelling, social psychology, attitude change, game theory,social network

I. Introduction

Studies currently conducted demonstrate the significance of opinion formation in social networks for a variety of domains, including political elections [3, 4], social governance [5-7], and word-of-mouth marketing [1, 2]. Online opinion creation has been a hot topic in nonlinear physics and sociology because it incorporates both psychological behaviour and network dynamics [8]. Opinion dynamics seeks to define various interaction mechanisms from individual levels in order to illustrate how societal beliefs change and converge. Generally speaking, an individual's opinion defines his attitude or stance towards a particular item [9, 10]. Despite the abundance of research on opinion models, the majority of them concentrate on statistical physics or nonlinear physics techniques [8], which are unable to accurately depict both group behaviour and individual brain activity. In actuality, the formation of collective opinion is a multifaceted and intricate process in which each person's ideas and actions must be taken into account. As such, modelling group opinion development at the individual level is quite important.

In order to address the issue, earlier research has relied on agent-based modelling, which is a largely effective technique in social dynamics and the foundation of many opinion models [8]. Many agent-based models have been presented since French first an opinion formation model in 1956 [11]. These models can be classified as continuous [12,13] or discrete [14–17] depending on how the opinion variables are described. The general framework of opinion models, whether continuous or discrete, can be summed up as follows: In a particular network, the views of the agents are initialised; at each time step, the agents interact with one another according to a set of rules and then determine whether to modify their opinions; eventually, the opinions of all the agents state[10] tend to find an equilibrium.

The agent's behaviour is influenced by both the group environment and interactions with others, as they are viewed as social beings rather than just nodes [18, 19]. Theories from sociology and psychology are also crucial sources of evidence for explaining how opinions are formed, both in terms of macro-level group behaviour and micro-level individual interactions. In particular, behavioural psychology theories such as stimulus-response theory [20] (subsequently refined as stimulus-object-response [21]) can be utilised to account for individual behaviours in the formation of opinions. This is because, if we consider opinions received as a stimulus, an individual's response is to determine whether or not to modify his opinion. Hovland's well-known attitude change model serves as a theoretical foundation for simulating an individual's mental state, with the option to alter one's attitude or adhere to one's point of view [22, 23].

Evolutionary game theory is a theoretical approach to group behaviours that has been extensively used in group dynamics [8,24]. Evolutionary games concentrate on how players consistently obtain the highest possible rewards through repeated gameplay. If we think of agents with diverse perspectives as players adopting different strategies, we may apply this concept of dynamic development to opinion formation [25]. The behaviour of each agent and its interactions with the group are detailed independently in evolutionary games, and as agents continuously modify their strategies—that is, their opinions—a shift from individual behaviour to group behaviour occurs.

We examine how topic type, parameter changes, and opinion leaders affect the formation of opinions based on data from Twitter. The findings indicate that there is more ambiguity and sustainability in the opinion evolution surrounding a contentious issue. Benefit to cost ratios have a big influence on how attitudes are formed; a moderate ratio will lead to the longest relaxing period or the most widely held beliefs worldwide. In addition, popular opinion might be influenced by celebrities more than by professionals.

II. Theoretical background

Opinionmodels

By specifying various interaction processes at the individual level, the opinion model seeks to provide a fundamental understanding of how social beliefs change and converge [9, 10]. These days, most opinion models can apply agent-based modelling because it is a widely utilised technique in social dynamics [8]. French first puts forth a model for opinion formation in 1956 [11].where the impact of network connection on group opinion shifts is also demonstrated, and continuous opinion is assessed using a ratio scale. Generally speaking, depending on how the opinion variables are defined, agent-based models can be classified as continuous or discrete. Typical discrete opinion models are the Sznajd model [14,15], Voter model [16], and Galam. Typical continuous opinion models are the Deffuant model [12] and the HK model [13].

The principles governing opinion interaction between agents vary amongst models. The voter model makes the assumption that at each time step, a person arbitrarily adopts a neighbor's viewpoint as their own [16]. Galam model presupposes that an agent will typically choose the group's most widely held viewpoint [17]. The bounded confidence approach, which maintains that agents could only communicate if their opinion difference is less than a threshold, is the foundation of the continuous opinion models such as the Deffuant model [12] and the HK model [13]. While some models take into account the social characteristics of actors or create opinion interaction rules based on actual social situations, the majority of them emphasisemodelling and simulation using statistical physical approaches or nonlinear physics.

III. The proposed model

A directed link from follower to leader indicates the following relationship in a directed social network, such Twitter or Instagram. Within a network like this, a leader's viewpoint filters down to his followers. We view opinions as binary, denoting two opposing viewpoints on a given subject, either yes or no. By converting the opinion receiving mechanism from unidirectional to bidirectional, the model can also be used to undirected networks.

The two components of the suggested model are collective evolution and individual persuasion. While the latter focuses on the dynamic evolution of group behaviours, or opinion strategies, the former seeks to provide a detailed illustration of the persuasion process of user-user pairs. One of the model's hypotheses is that the user's input might be obtained instantly.

Individual persuasion

Based on the stimulus-object-response theory [20], an individual's response is to choose whether to change his viewpoint if he views the received opinion as a stimulus. After getting leaders' opinions, the person will use his own analysis of the data to get a more thorough understanding than previously (Fig. 1). His later decision to either cling to his initial opinion or change his attitude will be influenced by this cognitive process, which will determine whether to strengthen or weaken it. Drawing from Hovland's theory of attitude change [22,23], we postulate that three factors influence a user's decision to be persuaded by his leaders (Fig. 2): the setting (group environment), the recipient's characteristics (person receiving opinions), and the leaders' credibility.

IV. Simulation results

Data description

Our dataset was obtained from Twitter and was made available by Arizona State University's Social Computing Data Repository [49]. Eighty million follow relations and roughly ten million nodes are present. We use a pruning procedure to iteratively remove leaf nodes from the social network until social networking features (average path length, average clustering coefficient, etc.) are clearly visible. The revised network's fundamental topological characteristics are displayed in Table 1, and as can be seen in Fig. 3, its in-degree distribution roughly follows the power-law distribution, a characteristic common to online communities.

Table1

Basic topological properties of the network.

N	M	<k>	D	L	C
12418	99087	7.979	15	4.747	0.132

Simulation of opinion formation

Influence of topic type

One of two categories can be found in online subjects: contentious themes or biassed topics. A controversial topic typically sparks heated debates within a group because it is the focus of significant public debate, disagreement, or criticism; in contrast, a one-sided topic initially garners consensus.

We model the process of opinion generation in the above Twitter network based on the proposed model. Benefit b and cost d are both set at 1, and coefficients $\tau1$, $\tau2$, and $\tau3$ are all set at the same value because the effects of knowledge, dependability, and stubbornness on benefit are all taken into account equally. Initialising to 1, the coefficients $\tau1$, $\tau2$, $\tau3$, ∂, and β all follow a normal distribution, meaning that $e(i) \sim N(\mu, \sigma2)$, where μ = 10 and $\tau2$ = 0.25.

The values of V(x), V(y), and V(i) are normalised from 0 to 1 in order to bring values measured on various scales to a notionally common scale. Two topics are simulated with consideration to topic type in order to see how different topic types affect the formation of opinions. When it comes to contentious topics, the initial opinion share (Opinion Share) is 55%, but for one-sided topics, it is 75%. Initially, at time t = 1, 55% (or 75% of users) are chosen at random to hold opinion A, whereas the remaining users hold opinion B. We model the formation of 100 opinions.

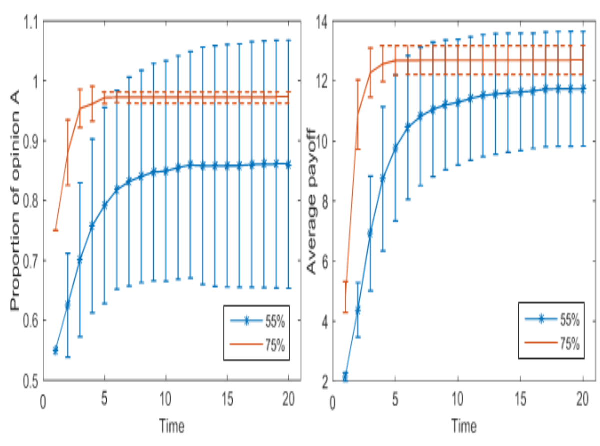

Figure1.shows how the average payment (right) and the percentage of users' opinions (left) change over time in the Twitter network. With error bars representing the standard

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deviation across 100 realisations, the data displays the mean value.

Times for every subject, then calculate the average outcomes. Figure 1 illustrates how the percentage of views A, The network's average payout varies over time.Figure 1 shows that the percentage of opinion A tends to rise quickly before stabilising and showing little variation. The network's average reward likewise exhibits an upward tendency until it stabilises. Furthermore, a contentious topic has a substantial result deviation across 100 realisations, whereas a one-sided topic has a very tiny deviation. More examples of initial opinion A proportions, ranging from 55% to 80%, are taken into consideration in order to investigate the impact of topic type on opinion development in detail.

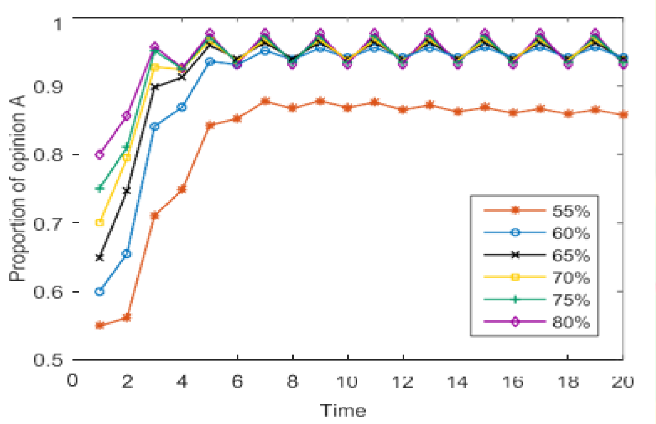

Figure 2: The percentage of opinions The initial proportion of A in the Twitter network varies with time step, ranging from 55% to 80%. The mean value over 100 realisations is displayed in the data.

Influence of parameter changing

The reward formula has four parameters: b/c, ∂, β, and $\sigma 2$. A person's benefit is indicated by b when one of the leaders supports their opinion, and their cost is indicated by c if they disagree; the coefficient for trustworthiness in Equation (1) is ∂; the coefficient for stubbornness in Equation (2) is β; the intermediate level of overall expertise is indicated by μ; and the degree of dispersion is measured by $\sigma 2$. μandβ can be disregarded since data normalisation makes them insignificant in relation to the outcomes. The initial percentage of opinion, A, is set at 55% in order to analyse the effects of b/d, ∂, and $\sigma 2$. The experimental results indicate that while changes in ∂ and $\tau 2$ have little influence on opinion(fig 2)formation, only b/c has a substantial effect.

This makes sense because coefficient ∂, as an exponent, increases a user's credibility as in-nodes (followers) rise; its value, however, solely influences how quickly this relationship rises. The dispersion degree of a group's competence is measured by the coefficient $\sigma 2$, whose value changes depending on the social community. However, it is evident that an issue will ultimately reach consensus in several communities, as supported by earlier research [10, 25]. Basically, b/c expresses how much benefit b has changed relative to cost c. To put it simply, the price is always set to 1, hence the only value that needs to be under control is b. If $b>$ 1, then it is more advantageous to share the same opinion than it is to have a different one.

V. *Comparison*

We contrast the output of our model with the most advanced models proposed recently (Table 4). Even though agents' opinions vary depending on the models they adopt, the social group would eventually come to an agreement on a particular viewpoint. It is further evidence that the ratio of benefit to cost has a substantial influence on opinion formation because there is an optimal ratio of benefit to cost in Ref. [25] that results in the shortest consensus time. Furthermore, as the average degree of the network rises, the consensus time lowers, underscoring the significance of in-degree in opinion steering. Furthermore, as our model agrees, Refs. [10] and [54] demonstrate how important the initial opinion distribution is to the evolutionary outcome.

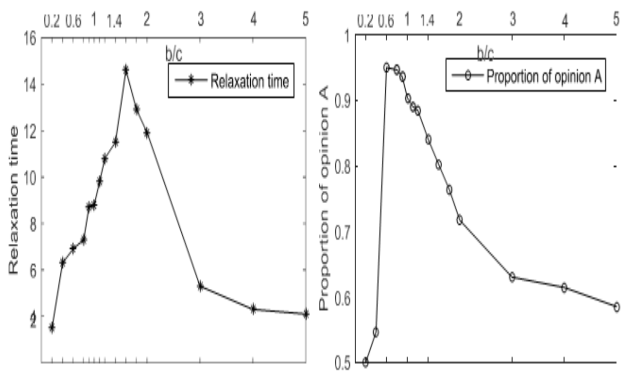

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Fig. 3.The relaxation time (left) and final proportion of opinion(right) as a function of*b*/*c*respectively,withthe initialproportion ofopinion*A*be 55%.

In the remaining three models, the propagation of opinions is influenced by network features, changing rules, starting opinion distribution, and agent rationality. However, these elements are intrinsic and difficult to regulate as a guiding solution. Users with a high in-degree have been shown to be effective in guiding the opinion trend in our model, and it is simple to apply. Actually, a lot of businesses follow this advice: vendors typically search for well-known people who have a big following on Twitter in order to advertise their goods there. Overall, the suggested model adds something new to opinion formation modelling after accounting for ideas from psychology and sociology, and some of the findings are corroborated by earlier research.

Table2

Model	Opinion updating basis	Converge	Optimal*b*/*c*	Result Effectiveguidance
Thispaper	Payoff	Yes	Exist	1)Highin-degreeagents
Ref.[5]	Payoff	Yes	Exist	1) Averagein-degree 2) Networksize 3) Lessnoise(irrationalchoices)
Ref.[12]	Payoff	Yes	Notdiscussed	1) Evolvingrule 2) Networktopology 3) Initialopiniondistribution
Ref.[14]	Bounded confidence	Yes	Notdiscussed	1) Initialopiniondistribution 2) Oppositeopinion

VI. Conclusion

In order to study the process of online opinion creation in social networks from the perspectives of sociology and psychology, this research presents an agent-based model. To construct the opinion interaction mechanism, group behaviour theory, attitude change theory, and evolutionary game theory are introduced with the understanding that the agent is a social man. In order to examine both the microcosmic individual interaction and the macroscopic group behaviour, the user's leaders consider factors such as recipient characteristics, group environment, and leader credibility when persuading them. Furthermore, we utilise evolutionary game theory to examine the dynamic shift in users' perspectives during the spread of a topic. Furthermore, our methodology takes into account the variety of the person by utilising both the stubbornness and the competence of the leader.
The suggested model is validated through our experiments using the Twitter dataset. Despite being designed for directed networks, our concept can also be applied to undirected networks by simply switching the opinion receiving mechanism from unidirectional to bidirectional. To examine how topic type, parameter changes, and opinion leaders affect the process of forming opinions, we run various simulations. The findings indicate that a more cohesive group's initial attitude shortens the time it takes to establish consensus and that opinion development for contentious topics acts more uncertainly and sustainably, leading to intense debate. Out of all the parameters, the benefit over cost ratio is the only one that significantly affects how opinions are formed, and the given ratios (about 1.6) results in the longest relaxation period.

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