Mining Social Networks for Dissemination of Fake News Using Continuous Opinion-Based Hybrid Model

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Abstract. The entire world is confronting the challenge of fake news disseminated online, as its consequences could be exceptionally catastrophic. In this paper, we have proposed a hybrid model that integrates the opinion evolution process with the propagation of fake news. The level of extremity in opinions, the amount of support from social connections and the social influence were used as the major design considerations in modeling the spread of fake news. As polarized opinions on social media often lead to polarized networks, the proposed model was utilized to study the effect of evolving opinion on the spread of fake news on polarized networks of varying degrees. Our findings suggested that there are more users involved in sharing fake news in the presence of a highly polarized network. Moreover, the tendency of a user to adapt the opposing opinion seems to be correlated with the exposure of fake news. Besides this, we also assessed the consequences of the spread of fake news on the user's opinion and found that the users that are mainly influenced are the ones having an unclear stance towards a given issue. Overall, our proposed model highlights the interrelation between fake news and the opinion evolution on social networks.

Keywords: Spread of fake news · Agent based modeling · Opinion dynamics · Network polarization

1 Introduction

Social networking sites like Twitter, Facebook and WhatsApp have gained enormous attraction among people across the globe. This popularity has come at a cost, i.e., these platforms are being used for sharing fake news [17]. Although, several measures have been taken by the social networking sites and the administration of different nations [1,17] to ensure the integrity of the content shared online. Despite these efforts, the problem of using the online medium to spread fake news persists [21].

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Several researchers have analyzed the dissemination of fake news based on different aspects such as the content of the news [19], the profile of the users engaged in spreading the news [15] or engagement of bots [14]. Besides these approaches, there is another area of research that aims to model the diffusion process of fake news. The process of modeling has been studied using different methods including the concepts of physics [8], natural phenomenons [9] and epidemiology [3]. The epidemiology-based modeling is considered to be an adequate method as the diffusion process of both infectious disease and fake news are quite similar in nature [10].

The spread of fake news on online platforms has often been linked with the polarized opinion of the users [4,18]. Furthermore, it has been found that users with similar opinions like to connect with each other and thus results in the formation of polarized communities within the network (or simply polarized network) [4]. These polarized communities then act as a deciding factor for the virality of the fake news on social media platforms [4]. Tornberg and Petter [18] also observed that the spread of misinformation is boosted by the existence of echo chambers within a social network. Here an echo-chamber corresponds to a closed environment where people perceive and amplifies opinion of their own. The existence of polarized opinions accompanied by fake news could even disregard social welfare activities such as vaccination [13].

As seen above, the majority of work studying polarization and fake news assumes opinion to be a static entity and hence does not incorporate the dynamics of opinion formation with the propagation of fake news. Although, recently Zeng et al. [22] studied the change in the state of emotion under the influence of the rumour refutation process. The refutation process was successful in transforming the state of emotions from negative to a positive or an immune state. Thus in their study opinion is represented through emotions, which could be either positive, negative or neutral, whereas our focus is on the continuous opinion and their evolution with the spread of fake news.

In this study, we have proposed a hybrid model to analyze the propagation of a post containing fake news, based on evolving opinions. The term "hybrid" is used for the model, as it combines the diffusion of opinion with the diffusion of fake news. The model uses the epidemic-based nature-inspired approach for modeling the spread and a bounded-confidence method for modeling the dynamics of opinion formation. The level of extremity in the opinions is considered to one of the key players, in the spread of fake news, during the design of the model [7]. The proposed model is used to establish a relationship between the polarized opinions and the spread of fake news, for networks representing a varying level of heterogeneity among users of different opinions.

Based on our knowledge, modeling continuous opinion with the diffusion of fake news for analyzing the effect of polarized opinion on the spread of fake news has not been done previously. The paper is organized as follows. The proposed model is discussed in Sect. 2. The findings related to the implementation of the proposed model on networks with varying degree of polarization are reported and discussed in Sect. 3. Finally, the overall conclusion of our study is provided in Sect. 4.

2 Proposed Model

In this section, we have discussed the design of an agent-based model[1] to identify the association between the spread of fake news and polarized opinions. As discussed previously, the opinion of an individual is an essential factor that facilitates in spreading of fake news on social media. Hence, we propose a hybrid model that collectively analyses the dynamics of opinion formation and the diffusion of fake news on social networks. For analyzing the dissemination of fake news, we have used the SEIR model [11], designed for assessing the spread of infection-based disease. Every agent in the hybrid model is considered to be in one of the following four states.

– **Susceptible (S)**: The state corresponds to those individuals that have not yet consumed the fake news.
– **Exposed (E)**: An agent which has consumed fake news but hasn't shared with others yet, is said to be in an "Exposed" state.
– **Infected (I)**: As the name suggests, those agents which have consumed as well as shared the fake news with their neighbours, are considered to be in an "Infected" state.
– **Recovered (R)**: The agents in this state can be considered to be those that have explicitly realized that the given news is fake by deleting the shared news.

For studying the propagation of fake news in combination with opinion dynamics, the hybrid model takes inspiration from a bounded confidence-based model [20]. In a bounded confidence based model, the opinion of an agent is considered to be influenced by the opinion of its neighbours, where only those neighbouring agents are considered that are similar in opinion within a certain threshold. In our proposed model, the opinion of every agent is updated on being exposed to the post containing fake news and the change in opinion of the agent is done following the principles of opinion similarity between an agent and its neighbours. The steps involved in the proposed model is explained in detail as follows:-

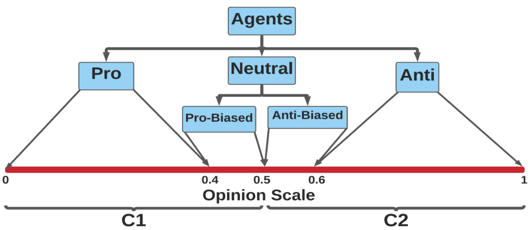

Fig. 1. Initialization of opinion of the agents.

[1] Code for the model is available at https://github.com/maneetsingh88/fakenewsModeling

2.1 Initialization

Opinion: The opinion O_i of an agent i is considered to be a continuous quantity i.e. $O_i \in [0, 1]$. The initialization process of opinion is divided into following two phase:-

Categorization: For a given issue, we have assumed, three categories of agents as shown in Fig. 1. The pro group corresponds to the set of agents supporting the issue with varying degrees (i.e. opinion from 0 to 0.4), on the other hand, the anti group corresponds to the set of agents opposing the issue (i.e. opinion from 0.6 to 1). The remaining agents belong to the neutral group. They are further divided into two subgroups- *pro-biased* and *anti-biased*. The agents with opinion from 0.4 to 0.5 are considered to have an unclear stance with relatively more social connections on the platform with the ones supporting the issue than those opposing it. We referred to these agents as pro-biased neutral agents. Similarly, agents with an unclear stance towards the given issue (i.e. opinion from 0 .5 to 0.6) and relatively greater connections with the anti group agents, were referred to as anti-biased neutral agents.

Assignment: For assigning the opinions to the agents, the given network was divided into two communities, say C_1 and C_2, using a community detection algorithm [2]. The two-community structure of a network has been observed for both controversial as well as non-controversial topic based social network [6]. Thus, the community C_1 would comprise of agents from pro and pro-biased neutral groups and similarly the community C_2 contains agents from anti and anti-biased neutral groups. Therefore, the opinion of an agent is assigned as follows:-

$$O_i = \begin{cases} rand(0, 0.5), & \text{if } i \in C_1 \\ rand(0.5, 1), & \text{otherwise} \end{cases} \tag{1}$$

where rand is the function that provide a random number within the given range from a uniform distribution.

This method of opinion initialization ensures that people with varying degrees of supporting or opposing the issue are uniformly distributed within the respective communities. As possible with any real dataset, the size of the two communities may not be the same. Therefore any observations made from the model should be done at an aggregate level through multiple simulations, with equally selecting one of the two communities for the propagation of fake news.

Social Influence: An individual's social influence is regarded as an essential factor in the virality of any post on social media. The post shared on social media by highly influential nodes (i.e. those having large number of followers) has a far reach among the users of the platform. Thus, the degree D_i of an agent i in the given network is used to compute the social influence as per the following equation:-

$$S_i = \text{norm}(D_i) \tag{2}$$

where norm is a scaling function applied to ensure $S_i \in [0,1]$, without affecting the degree distribution of the network.

Extremeness: The extremeness attribute of an agent is derived from its opinion. It measures the closeness of any agent towards one of the ends of the opinion spectrum. The extremeness E_i of an agent i is computed using the following equation:-

$$E_i = abs(2 * O_i - 1) \tag{3}$$

where abs is a function used to find the absolute value of the given number.

Group Support: The level of support an individual possess from its social connections could greatly influence the decision to express an opinion publicly. Here expressing an opinion is associated with sharing a post on social media platforms. The group support G_i for an agent i is computed as follows:-

$$G_i = \begin{cases} |P|/D_i, & \text{if } O_i \leq 0.4 \\ |A|/D_i, & \text{if } O_i \geq 0.6 \\ |N|/D_i, & \text{otherwise} \end{cases} \tag{4}$$

where

$$P = \{i \mid O_i \leq 0.4\} \quad \forall i \in Ag$$
$$A = \{i \mid O_i \geq 0.6\} \quad \forall i \in Ag$$
$$N = \{i \mid O_i > 0.4 \text{ and } O_i < 0.6\}$$

In the above equation, P, A and N represents set of agents belonging to "pro","anti" and "neutral" group respectively, whereas Ag denotes the set of all agents.

State: Initially every agent is assumed to be in a "susceptible" state, i.e. they are unaware of the fake news.

2.2 Propagation

The actual spread of the post containing the fake news, into the network, takes place in this phase. First, one of the agents is selected as an initiator of the fake news. The state of the selected agent is changed from "susceptible" to "infected". At each step k of propagation of fake news, an agent's opinion as well as state is updated as follows:-

– If an agent i is in a "susceptible" state and one of its neighbour j is infected, the opinion of an agent i is updated on seeing the post from its neighbour j, based on the following equation:-

$$O_i^{(k+1)} = \begin{cases} O_i^{(k)} + 0.2 * M_i * \Delta O & \text{if } \Delta O \leq \epsilon \\ O_i^{(k)} & \text{otherwise} \end{cases} \tag{5}$$

where $M_i = 1 - E_i$ represents the degree of moderation of an agent i and $\Delta O = O_j - O_i$. Thus, the opinion of an agent i will be influenced by its neighbors' self opinion (O_j), only if O_j is similar to its own opinion (O_i) within the given threshold (ϵ). Apart from updating the opinion, the given agent will enter the "infected" state based on the probability α, given as:-

$$\alpha = \begin{cases} (S_j + E_i + G_i)/3 & \text{if } \Delta O \leq \epsilon \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

In case of state transition from "susceptible" to "infected", the opinion of the neighbour posting the fake news needs to be similar to an agent's self-opinion. The value of the state transition probability i.e. α for agent i is computed with the assumption that the extremeness of opinion(E_i), social influence (S_j) of the neighbour j and the tendency to incline towards self-belief (G_i) are the major drivers of dissemination of fake news online [7,21]. We have computed and assessed the state transition probability for every infected neighbour j separately and thus an agent with a large number of infected neighbours, has larger chances of getting infected [18]. In case an agent does not move to an infected state in the current step even after having at least one infected neighbour, then it is automatically moved to an "exposed" state.

- If an agent i is in an "exposed" state and one of its neighbours is "infected" then the agent will update its opinion and stochastically its state, based on the procedure discussed above.
- If an agent i is in an "infected" state then it will move to a "recovered" state based on a probability β. This transition could be considered as the case where an agent deletes its post and hence will no longer infect or spread the news to its neighbours.

The propagation phase of the model is repeatedly executed until equilibrium, i.e. when there is no change in the opinion as well as the state of each agent. The value of both ϵ and β was experimentally kept fixed at 0.2. The purpose of keeping the value of ϵ low is quite intuitive, as higher values would have eradicated the issue of polarized opinions [18,20]. Similarly, for β, there has been a previous study [5], which found the probability of deleting the post not more than 0.2. Although in the upcoming section, we have also analysed and reported our findings on varying the values of these parameters. The overall workflow of the model can also be seen in Fig. 2.

3 Results and Discussions

In this section, we analyzed the role played by the polarized opinion of users in the spread of fake news. Therefore, the proposed model was simulated on three different networks (Fig. 3) to compare the spreading behaviour of fake news on different levels of network polarization. The first network is the follower's network of users engaged in discussing Article 370 on Twitter, obtained from our previous study [16]. We will be referring to this network as a "Real" network

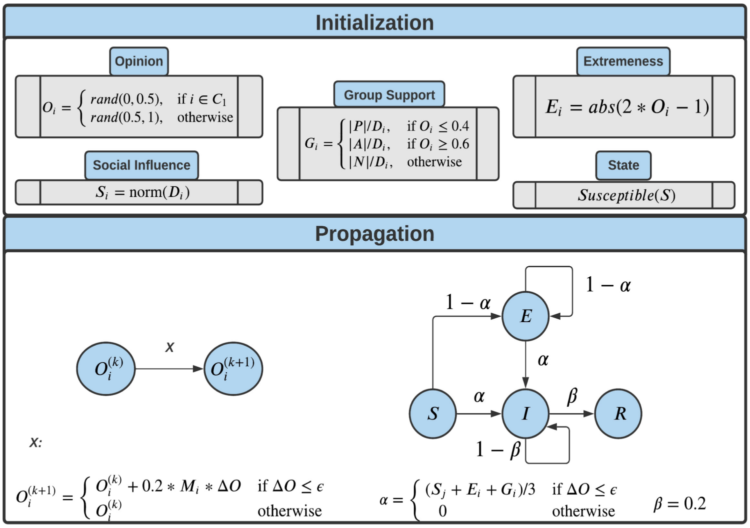

Fig. 2. Opinion-based hybrid model for propagation of fake news on social networks.

in our future discussions. The "Real" network was then used to construct the other two networks. In this regard, we first divided the "Real" network into two communities say C_1 and C_2 [2]. Subsequently, the second network was constructed by adding 1000 edges (around 20%) within both the communities (i.e. 500 edges to communities C_1 and C_2 separately). In order to construct our third network, we added a similar number of edges (i.e. 1000) between the community C_1 and C_2 in the "Real" network. As both the networks were obtained by adding either intra-community connections or intra-community connections within our "Real" network, we will refer to them as "IntraCC Real" network and "InterCC Real" network respectively in our future discussions. The reason for adding intra-community edges is straightforward, more connections among users belonging to similar communities, more chances of communication between them and similarly more chances of polarization. The purpose of adding connections between two communities is just the opposite, where these connections might facilitate more communication among nodes of different communities and thereby might reduce polarization. To verify that the network polarization of "Real" network is increased by "IntraCC Real" network and decreased by "InterCC Real" network, we computed the heterogeneity scores for both the network [12], which comes out to be 0.09 and 0.78 respectively. The very low heterogeneity score for "IntraCC Real" network indicates that the network is extremely polarized and very high heterogeneity score for "InterCC Real" network shows that it is "non-polarized". The reason for synthetically generating the networks using the "Real" network is two-fold. First, we will have a similar set of nodes to assess and second, by doing this, we could easily quantify the difference in the spread of fake news by varying the network polarization. The basic details of the networks are shown in Table 1 and the degree distribution is shown in Fig. 4.

Now with these networks at hand, we want to execute the model proposed in Sect. 2 on these networks. Since the originating fake news can lie on any side of the opinion spectrum, hence the model was simulated 1000 times by selecting the opinion of the fake news as either "pro" or "anti" in equal share. If "pro" is selected then a node from the "pro" group is assigned as the initial spreader of the fake news and vice-versa. This approach ensures that the final results are not biased towards either of the opinions. The effect of different networks on the visibility and the spread of fake news can be seen in Figs. 5 and 6. The overall visibility of fake news is higher for the "InterCC Real" network, which is mainly due to the non-polarized nature of the network. In the case of the "Real" and "IntraCC Real" networks, there does not seem to be any difference in the final visibility level of the fake news. This could be due to the fact that, both the networks are overall polarized. Similarly, in terms of spread, a network with higher polarization has a higher spread of fake news, which is in line with previous research [18]. These results highlight the impact of polarized opinion on the diffusion process of fake news in networks with varying levels of polarization.

The effect of the initial opinion of the initiator of fake news on the overall spread is also studied and results are shown in Fig. 7. It can be observed that our previous results hold irrespective of the initial opinion of the first spreader. The visibility of fake news is higher for a non-polarized network and is independent of the initial opinion of the originator of fake news. In the case of the spreading pattern, "IntraCC Real" network has the highest number of posts shared, followed by "Real" network. Thus, it seems that users like to spread fake news that aligns with their stance irrespective of the degree of extremeness in the opinion of the initiator.

Table 1. Basic properties of "IntraCC Real","Real" and "InterCC Real" Networks (Deg stands for degree, CC stands for clustering coefficient and het stands for heterogeneity).

Network	#Nodes	#Edges	avgDeg	avgCC	hetScore
IntraCC real	1606	6934	8.63	0.20	0.09
Real	1606	5934	7.40	0.23	0.17
InterCC real	1606	6934	8.63	0.15	0.78

The effect of the conformity bias (ϵ) and the likelihood of explicit recovery (β) on the overall visibility and the number of users sharing the fake news are also evaluated (Figs. 8 and 9). The level of conformity bias seems to be associated with the visibility of fake news. As we increase the value of the ϵ, the level of exposure and the number of spreaders both increases. In the case of the parameter β, the explicit deletion of the shared post, do not make major changes to the exposure of the fake news within the social network and hence we can say that the damage was already being done.

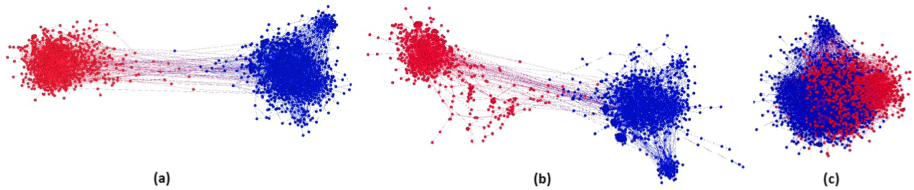

Fig. 3. Visualization of (a) "IntraCC Real", (b) "Real" and (c) "InterCC Real" networks.

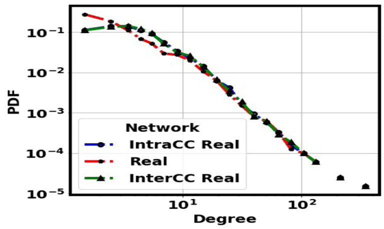

Fig. 4. Degree distribution of "IntraCC Real", "Real" and "InterCC Real" networks.

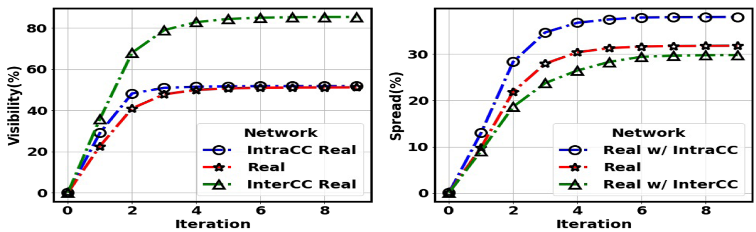

Fig. 5. Cumulative proportion of visibility and spread of fake news with time.

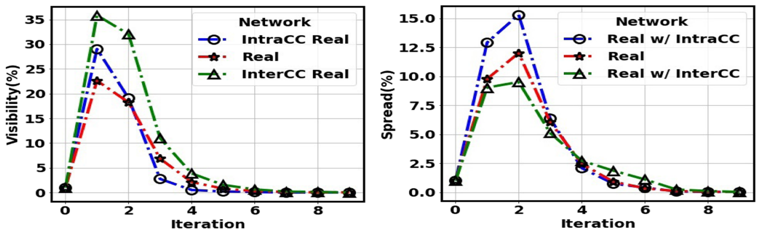

Fig. 6. Step-wise proportion of visibility and spread of fake news with time.

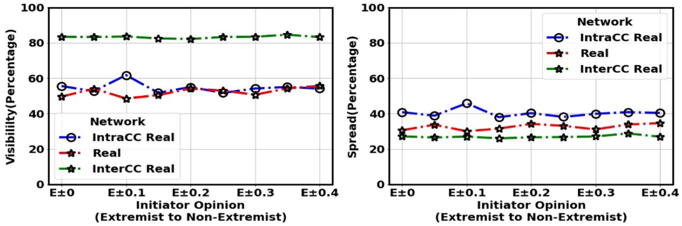

Fig. 7. Proportion of visibility and spread on varying the opinion of the "initiator" node from both sides of the spectrum. Here E represents Extremism either for "pro" or "anti". In case of "pro" it should be read as 0, 0.1, 0.2, 0.3 and 0.4. For "anti", it should be read as 1, 0.9, 0.8, 0.7 and 0.6. The results are aggregated for "pro" and "anti" opinion, for example E $\pm$ 0.1 is an average for 0.1 in case of "pro" and 0.9 in case of "anti".

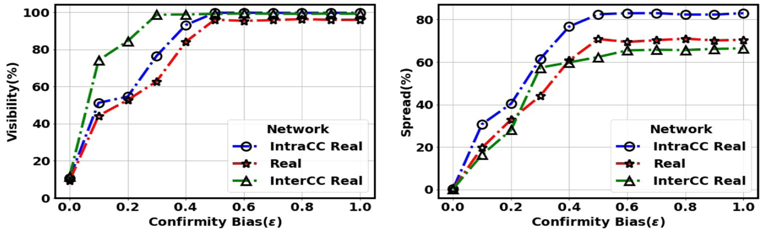

Fig. 8. Effect of varying conformity bias on the visibility(V) and the spread(S) of fake news

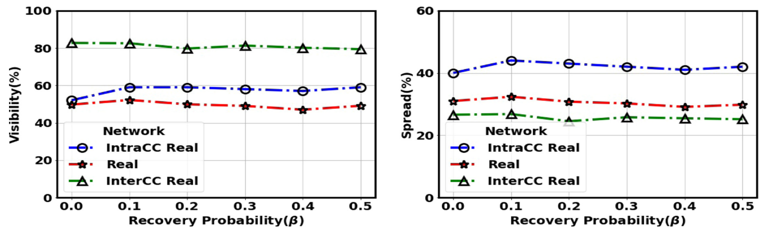

Fig. 9. Effect of varying recovery probability on the visibility(V) and the spread(S) of fake news

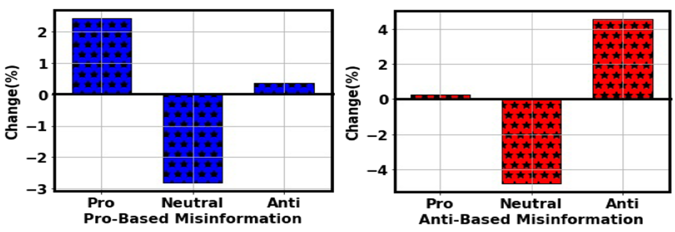

Fig. 10. The share of users belonging to "pro","neutral" and "anti" group before and after the diffusion of "pro-based" and "anti-based" fake news.

Next, we aim to study the effect of fake news on opinions at a macroscopic level. It has been reported that fake news campaigns can play a vital role in manipulating the voter's decision during the elections [7]. We want to verify whether our model can identify such associations between the change in opinions and the spread of fake news. Therefore, the proposed model was executed on the "Real" network. For the sake of simplicity, the change in opinion is analysed categorically using "pro", "anti" and "neutral" users (Fig. 10) for both kinds of fake news, i.e. supporting and opposing the given issue. The results indicate that there are more number of users in the "anti"("pro") group after the spread of fake news depicting "anti"("pro") opinion. This change seems to be mainly due to the shifting of users with a neutral opinion towards the opinion side depicted by the post containing fake news. Thus, users with an unclear stance seem to be more vulnerable to be influenced by fake news.

4 Conclusion

In this paper, we have analyzed the spread of fake news on social networks, by introducing a hybrid model for assessing opinion evolution with the spread of fake news. Specifically, we examined the effect of varying degrees of network polarization on the spread of fake news, when opinion is considered to be a dynamic as well as a continuous entity. The higher level of polarization in the network causes more users to share fake news. The conformity bias seems to be directly correlated with the spread of fake news. The efforts by spreaders to repudiate by deleting the shared post do not significantly affect the exposure of the post containing fake news. We have also observed the impact of fake news on the opinion of the users in a social network. In this study, we have focused on fake news that our polarized in nature, but in the future, we would like to extend the model to incorporate generic fake news on a large network of users on social media to make it more robust and practical. Overall, the findings of our study highlight the dynamic nature of opinion and its role in the spread of fake news on social networks. Hence, any model for analysing the spread of fake news must integrate the process of opinion evolution.

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