Are Misinformation Propagation Models Holistic Enough? Identifying Gaps and Needs

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Abstract

Misinformation has experienced increased online diffusion, mainly due to the low control of published content and low interest in fact-checking it from social media users. Many efforts have focused on misinformation-related tasks, although typically centered on one perspective, such as shared texts or users' connections. There is a lack of holistic integrations of these local and global perspectives. Misinformation propagation models allow us to simulate how misinformation spreads through social media, and they are a way to combine both of those dimensions. In this work, we present a comprehensive study of the state of the art in this task to highlight these approaches' limitations and to establish the requirements for these models to approach misinformation propagation from a more holistic perspective.

Keywords

Rumor Propagation, Fake News, Multi-agent Systems, Epidemiological Models

1. Introduction

Misinformation has proven to have a perverse effect by manipulating the public through different techniques, such as appealing to their emotions or fears to foster its believability [1]. It has negatively affected democratic processes, such as the 2016 and 2020 US Elections [2, 3], and spread potentially harmful content, such as the misinformation regarding the COVID-19 pandemic [4]. Many efforts are underway to determine what distinguishes fake content from other information [5], to detect its presence [6], or what users are more susceptible [7]. At the micro level, fake news detection is addressed by analyzing the information within a message. Recent efforts exploit Large Language Models (LLMs) [8] for their enhanced performance. Other methods have explored the detection from a more rounded standpoint, exploiting characteristics from Twitter (now X) threads [9], such as the depth of the tree, or subjective metrics such as biases and credibility [10], outperforming state-of-the-art models.

At the macro or social network level, there have been efforts to detect profiles sharing misinformation [11], showing that information on user interactions improves results obtained using only user information. The detection of bots is also explored through user features and network topology [12], showing how bot formations foster high propagation rates. It has also been approached from the lens of the differing stances within communities [13]. These features, from user characteristics to network topology, prove informative for these tasks [14].

From these efforts, we notice a general lack of holistic integration. Some approaches to detect spreaders have integrated information from different levels [15], such as shared information, user profiles, and ego networks. Nonetheless, most efforts focus on disjointed perspectives, either local [8] or global [12]. Holistic integration might limit the risk misinformation poses [16], especially considering the complexity of organized campaigns. Propagation models, which allow us to simulate how misinformation disseminates online, are a way to combine both dimensions.

There are significant efforts toward modeling the users and their psychological capabilities or behaviors [17, 7], although none includes the shared information. Some approaches have considered

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the topics of the messages, their emotion, or users' common interests [18, 19, 20], disregarding the value of the content by itself. Regarding the macro level, most efforts employ synthetic networks [21]. Other approaches have used real topologies without the matching shared information [22], although it is crucial to the diffusion [23].

As it becomes apparent, misinformation has been commonly studied from the perspective of separate signals. Although propagation models present an opportunity to connect them, there is still a lack of research. The content of the shared information plays a significant role in the diffusion [24], differing from real information [25]. Current efforts disregard this component, which seems counterintuitive, given that the users interact with a message, textual or otherwise. With this work, we aim to highlight current limitations within these models, affecting their holistic integration and exploring the requirements for proper experimental frameworks.

This paper is structured as follows. We review state-of-the-art propagation models in Section 2. In Section 3, we expose their limitations, and in Section 4, we identify the requirements for these holistic models. Finally, in Section 5, we highlight our conclusions.

2. State of the Art

This section reviews the state-of-the-art propagation models. We start with early approaches in Section 2.1, then continue with epidemiological-based models in Section 2.2. In Section 2.3, we introduce non-epidemiological models, while Section 2.4 covers agent-based social models.

2.1. Early Approaches

Based on ordinary differential equations (ODEs), epidemiological models have been extensively employed to study the diffusion of a virus within a population [26]. These models introduce one or several infected individuals into a population. The disease spreads amongst those susceptible until it has affected the whole group, or its diffusion slowly stops. These models divide the population into exclusive categories: *Susceptible*, *Infected*, and *Removed*. These are the states the users are in regarding the disease, and they give this model its name: the SIR model.

One of the first approaches to information diffusion adapts this epidemiological model [27] as an "intellectual epidemic", initially devised for its application in Information Retrieval. This approach creates a simile between the spread of a disease and the dissemination of information. Using the concepts in the epidemiological model as an analogy, the disease is now an idea or a piece of information, and the individuals are readers waiting to come into contact with it.

Stemming from the initial epidemiological model [26], other variations were proposed, such as the Daley-Kendall (DK) or Ignorant-Spreader-Stifler (ISS) model [28], including rumor-specific concepts, such as a decay rate to symbolize the forgetting of the information or its "news value". A later adaptation, the Maki-Thompson model [29], simplifies the former by altering the rate at which spreaders turn into stiflers.

These previous models, and others in this section, might rely on stochastic or deterministic processes. In a stochastic process, the transitions between the compartments are probabilistic (finite-state Markov Chain). In a deterministic model, transitions are expressed through differential equations. A deterministic model is simpler than a stochastic one. However, it presents some drawbacks, such as the transition rates being proportional to the population size [30] and not allowing for individual behavior or network heterogeneity. Stochastic models incorporate randomness and are also more realistic [31], at the cost of higher complexity [27].

2.2. Extension of Epidemiological Models

Based on the previous models, a formal definition of information diffusion we will use for these next sections corresponds with the interactions between a population of N individuals, with an underlying graph (directed or undirected) $G = (V, E)$ for a set of vertices $V = \{v_0, ..., v_{N-1}\}$ and a set of edges

$E = \{e_0, ..., e_{E-1}\}$ that connects them. A node represents a user, and the edges between the users denote the connections, either explicit (follower-followee relationships) or implicit (interaction-based). Diffusion would be measured in users' internal stance (state) regarding the information per time unit.

Many other models inspired by epidemiological diffusion have been proposed since its early approximation, adapted to rumor diffusion, such as the *Susceptible-Infected* (SI) model [32], where users carry the information forever. The *Susceptible-Infected-Susceptible* (SIS) model [33], where the population would become *Susceptible* again, reflecting that users might forget the information. Lastly, the *Susceptible-Infected-Recovered-Susceptible* (SIRS) model [34] considers the possibility of gaining immunity after going through the infection (*Recovered*), and the possibility of losing it after some time (*Susceptible*).

These models face the problem of a clear divergence between information and epidemic transmission and the complexity of the former. Information diffusion depends on many factors, such as network topology or social interactions. Epidemiological models work on the assumption of a homogeneously interacting population, which contrasts with complex social media networks, facing unexpected deviations from the results obtained in epidemic fields [35, 36]. Another shortcoming involves the compartments for the population. Individuals might not get *Infected* but rather turn *Fact Checkers* against misinformation or undergo a period of indecision. Due to these limitations, other models aim to include complex factors not directly extracted from epidemiological behaviors but inspired by their interactions.

In the *Susceptible-Exposed-Infected-Recovered* (SEIR) model [37], individuals might go through an *Exposed* state after being in contact with an *Infected* node. Some variations consider the fuzziness of a rumor and a hesitating mechanism before sharing [38], a *Skeptic* state where users never share the information received (SEIZ) [39], or a transition to a *Recovered* state (SEIZR) [40]. The *Susceptible-Known-Infected-Recovered* (SKIR) model [41] creates a state for the individuals that spread the anti-rumor, drawing inspiration from evolutionary game theory for users' behaviors. Also modeling their opinions, the *Susceptible-Positively Infected-Negatively Infected-Recovered* (SPNR) model [42] includes two different stances towards the rumor: *Positively* or *Negatively Infected.* Regarding their emotion, the Emotion-based SIS model (ESIS) [19] classifies the message into seven differently weighted classes, such as fear or happiness, thus rendering some emotions more effective for spreading.

Other more complex models consider more states, such as the SCNDR model [43], where *Susceptible* users in this model might turn *Credulous*, *Neutrals*, or *Denies*, as well as turn *Recovered.* Besides believing the information or not, individuals might share it, not act or warn other users. The ICSAR model [44] considers the states: *Ignorant*, *Carrier*, *Spreader*, *Advocate* and *Removed.* These states can be further classified based on whether their information is a rumor or the truth. While users might transition between the different states and stances, *Advocate* and *Removed* are sink states, thus reflecting how users might not be persuaded to change their opinion.

As it becomes apparent, many models have drawn inspiration from epidemiology studies. Although they have been extended to account for information diffusion particularities, they still struggle to reflect intricate behavior. Dividing the population into compartments simplifies the problem, but it faces the difficulty of reflecting complex social behavior with a discrete label. As an example, in the $IS_1S_2C_1C_2R_1R_2$ model [45], the difference between the *Super Authoritative* and *Authoritative* or *Super Rumor Spreader* and *Rumor Spreader* states might have more to do with node qualities and network position rather than a state in a finite state machine.

2.3. Non-Epidemiological Models

Although epidemiological models have been extensively used in information diffusion, other mathematical models have been proposed. Some include *Independent Cascades*, the *Linear Threshold Maximization* model, or *Hawkes Processes.*

Independent Cascades start with a set of active nodes [46]. With each step, they might activate other surrounding inactive nodes with a set probability dependent on the connecting edge. There is only one chance for a node to activate its neighbors. This model has been used in the diffusion of information [47], showing that the dynamics can reflect those of social media [48, 49]. Other variations do not limit influence to a one-time-only event but a window [50].

The *Linear Threshold* model [51] establishes a threshold of surrounding neighbors for the users to change their behavior. Once a node is active, it cannot be deactivated. Other variations introduce weights between the nodes to account for social dynamics [52]. Further adaptations also introduce user information and the similarity between previously shared content [53].

Multivariate Hawkes Process is a type of stochastic point process model characterized by its ability to self-excite. *Hawkes Point Process* model was originally proposed to investigate earthquake events [54]. These models have been used for information diffusion on social media [55] and to devise how to mitigate its effects [56].

There are other lesser-known models, such as *Push-Pull* [57], which employs a pair-wise interaction where the user shares their information to attempt to "push" or "pull" others. *Markov Chains* have also been explored for this task, both discrete-time [58], and continuous-time [59].

These previous models are more commonly *Influence Maximization* problems. Normally, a higher-level controller supervises the optimization and the simulations, so individuality is limited. Additionally, some of these problems are NP-Hard. Although there are many efforts towards its reduction and optimization [47, 50], time complexity is high.

Beyond the epidemiological analogy, other models have been proposed inspired by different naturally occurring phenomena. Such is the case of the *Energy Model* [60] and the *Forest Fire Model* [61]. The *Energy Model* is based on the physical theory of heat energy. This model alters the traditional paradigm of a binary value for the diffusion, whether the user is infected or not, and leverages a continuous range of agreement with the rumor, constituting their "energy".

The *Forest Fire Model* [61] is influenced by the process of fire spreading in a forest. Drawing inspiration from the diverse factors that affect the formation and spread of fire, it creates a simile with social interactions. The forest density relates to users' ego networks, and the area's topography relates to the account activity. Further extensions allow users to receive the information without sharing it and a similarity score between them to assess their probability of sharing [18]. Although textual characteristics are included, they are used to model the users to establish similarity scores through matching keywords, not as part of the shared content.

2.4. Agent-Based Social Models

A more recent trend is to exploit the potential of Agent-Based Social Systems (ABSS). Most previous models assume homogeneity in user behavior, influence, or topology, which is limiting [30]. ABSS also adopts compartmental epidemiological models while solving those issues.

The SIR epidemiological model has been adapted to ABSS technologies [62]. This model considers *Infected* users might get *Cured* by realizing the rumor is fake and stop sharing. Other studies distinguish malicious and regular users and study their influence and susceptibility based on a belief system [63]. Similarly, it has been extended to account for bots and influencers with different behaviors [64], as well as time dynamics or trust measures between agents [65]. These approaches face the problem of only focusing on user-specific characteristics.

Other efforts have modeled individual processes in users' perceptions, such as an uncertainty-based SIR model, where uncertainty is modeled through ambiguity and ignorance [66], or a cognitive-inspired model where belief is measured based on dissonance and exposure [67]. Other common social effects and theories, such as homophily or social influence, have also been studied, such as a segregation between gullibles and skeptics within the population [68], aiding the spread of a rumor, or social context based o similarity and influence propagation [69].

Social sciences have been another interesting topic of research. The Big Five model [70] has been estimated to explore user similarity [20], homophily regarding political views [21], or a trust model based on users' identity, behavior, and relationships [71]. Game theory and decision theory have also been studied in the context of fake news [7], introducing common deception strategies to benefit from the uncertainty. Social Impact Theory has also been used for modeling rumors [72] by introducing other components such as persuasiveness or environmental bias. Lastly, echo chambers are also explored from different levels [17]: individual, environmental, and technological. Based on their experiments, the individual level is enough to polarize the networks, but adding the other two components generates more distinct groups.

The last and more recent approach exploits the capacity of large language models (LLMs) to simulate the opinions shared [73, 74]. Each agent potentially has different individual traits, personalities, and memories, and they can engage in discussions where they can reflect on their opinions and update them as needed. This new framework allows for fully customizable and rich environments to simulate how disinformation spreads.

An advantage of these approaches is the ability to test complex social-based behavior, such as simultaneous information [75] or real discussions between the agents. Although mathematical models have been used with centralized and decentralized measures [22], ABSS is more versatile and has been studied further in this context to identify influential nodes and delay the diffusion process [76], to study the simultaneous spread of a rumor and its counterinformation [75], and other measures based on user attention [64]. The main problem in many of these studies is the lack of real data validation. When including some of these social theories, the need arises to determine information from the user that might not be easily extracted or determined. This forces the models to employ estimations or distributions, which introduce biases.

3. Current Limitations

Propagation simulation models have some limitations, which affect their holistic integration. We can summarize them based on the five main areas we explore below.

Users. Whenever users are characterized, their metrics are established through probability distributions or means that cannot be validated, partly due to their complexity and the difficulty of extracting them from real data. Some proposals also employ psychological models without contemplating that associations between social media usage and these traits are not always found [77]; they might not align with the modeled behavior, or they might vary over time.

Content. Users have been the main focus in this area. Few studies consider the message through incomplete dimensions [78] or to establish user similarity based on posted content [18]. As such, content within the diffusion has not been explored. There is also a very pointed focus on the dichotomy of fake and real news. A priori, information is unverified and might remain so. Focusing on the characteristics rather than the truth value seems more realistic and valuable.

Network. In most cases, the topologies used are synthetic or do not match the real diffusion. This makes it impossible to connect users with their characteristics and topology, although it is an essential component. Another limitation is creating a network with as many users as participants in the conversation, which already creates an implicit bias. Although it would be computationally impossible to include all the users in any social media network, only including those participating makes another issue arise: predicting when users will not participate.

Internal state. Most studies measure interaction based on states, which reflect an internal measure of the users participating in the diffusion. Messages are used to make an abstraction of the users' state. This also allows intermediate states to reflect user behaviors that cannot be found in the real data. This situation can be avoided by using the messages directly, reflecting diffusion more accurately since users can share more than one message, but their state would remain a bounded constant. Messages were only employed in one study [63], aggregating diffusion into zero messages, over 500, and in-between. This would suggest that 500 retweets have the same relevance as 50.000, which should not be correct.

Evaluation. In most cases, validation is done through empirical evaluation or the analysis of mathematical properties of the diffusion within the networks. Although mathematical properties provide a theoretical background, real complex networks are characterized by their non-trivial features, which do not appear in synthetic graphs. Regarding empirical evaluation, incomplete data is most commonly employed, which forces the issue of its validity. Some approaches have been evaluated aggregating at the time level [63], which dismisses how relevancy works in social media: 500 retweets

Dataset	Content	Temporal	Network	User	Stance	Topic
FakeNewsNet[79]	✓	✓	✗	✓	✗	Politics
Palin and Obama[80]	✗	✓	✗	✓	✓	Politics
ReCOVery[81]	✓	✓	✗	✓	✗	COVID-19
CoAID[82]	✓	✓	✗	✓	✗	COVID-19
MediaEval[11]	✓	✗	✓	✗	✓	Conspiracies
PHEME-9[83]	✓	✓	✓	✓	✓	General
SNAP[84]	✗	✗	✓	✗	✗	-

Table 1
Available datasets for information propagation models and their main characteristics

in 10 minutes do not equate to 500 retweets in 10 days.

4. Requirements for a Properly Experimental Framework

A proper experimental framework is required to overcome propagation models' limitations. Within this empirical evaluation, it is important to recreate the scenarios of a news piece's diffusion on social media. Datasets that contain the necessary information to evaluate the models are crucial. Below, we explore the most relevant information required for this process.

Information of the shared content (**Content**) and the users (**User**). The information shared is an essential part of the diffusion. This includes the initial post, external website links, or visual content. In terms of the users, since they are the main focus of these models, it is important to have enough information on user metrics and engagement to properly characterize them.

Temporal information of when the texts are shared, by whom, and which users engage with it at what given times (**Temporal**). Besides the texts, we need to know the timestamps of when those posts are shared to determine the evolution of the news: whether more information is added or corrected, as well as how many times it appears at different times. Within the simulation, it determines when users are engaging, which is crucial for the evaluation.

The social network (**Network**). This is an important element in the diffusion of content online. Although synthetic networks might reflect some properties of real social media networks, they pose a significant limitation since diffusion inherently depends on those connections. Users with millions of followers will have higher chances of broadcasting information than new users.

Posts labeled with their stance (**Stance**). This is a relevant measure to study and evaluate diffusion in terms of epidemiological-based models. Distinguishing between *Infected* and *Vaccinated* is essential, equivalent to users' stance towards a post (*Support* or *Oppose*).

After establishing these requirements, we review available datasets to determine their suitability. In Table 1, we include the most relevant ones we found and their relevant characteristics. We have excluded datasets created ad-hoc since they are not publicly available and typically require retrieving new data and those centered around topics unrelated to misinformation.

As illustrated in Table 1, most datasets focus on the **Text** and **Temporal** aspects (the tweets and timestamps), and the **User** information from the poster. Some datasets, such as MediaEval, anonymize the tweets by removing the time when tweets were posted and removing the information from the users. These features are essential to establish the diffusion of information. Regarding this type of content, the SNAP collection does not provide diffusion information; it only shares the topologies from social media networks. Although it is valuable information, the diffusion that matches the network is deemed necessary. Some other collections, such as PHEME-9, include information regarding the users' state or stance towards the information. This information is also essential to evaluate epidemiological-based models.

Only two of the listed datasets include **Network** information associated with the diffusion: PHEME-9 and MediaEval. Medieval poses an additional problem due to its topology, created based on an interaction network. It is also significantly filtered and skewed: 3,800 tweets are associated with a network of 1.7

million nodes and 270 million edges. Based on these available resources, we can see that most current available datasets do not provide enough information for a proper evaluation. This is an important limitation and highlights the need for more publicly available content for the community to further research efforts into mitigating fake news.

5. Conclusions and Future Work

Current misinformation-related tasks and approaches show a clear divide between the micro level, or the content of the information, and the macro level, or the social network. There is a lack of holistic integration between the different tools to address misinformation. Propagation models are one tool that would allow a holistic approach by studying the diffusion of online misinformation from local and global perspectives.

With this work, we have studied current approaches to propagation diffusion models, from early approaches with the SIR epidemiological model to non-epidemiological models, such as the *Forest Fire* Model, and agent-based systems. From these approaches, we have appreciated some common limitations that constrain the holistic view. Within these constraints, the most relevant one is disregarding the information shared within the network, treated as a black box. To overcome these limitations, we have determined the main requirements for a proper experimental framework that would allow us to overcome them.

In terms of future work, we believe it is paramount to focus on overcoming these limitations by developing new models that consider the impact of the messages on the users. Additionally, posing new evaluation frameworks that overcome the limitations of the users' stances, such as focusing on the messages, is another interesting research avenue. Lastly, developing new publicly available datasets with the required information for these models is crucial for evaluating these models.

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