THE ROLE OF SOCIAL NETWORKS IN THE SPREAD OF FAKE NEWS

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Crises in human society have been accompanied by the deliberate and unintentional spread of false news since the time of ancient Egypt. However, the spread of misinformation has taken entirely new dimensions with the emergence of online social networks. According to the World Economic Forum, fake news represents one of the main threats to human society. The scope and speed of the dissemination of fake news and misinformation in today's world significantly negatively affect democratic processes. In this contribution, we present an overview of research on the spread of fake news on social networks, focusing on major global crises in recent times, such as the U.S. elections, the Covid-19 pandemic, and the war in Ukraine, and present the state of our ongoing research project in this field.

Keywords: misinformation, fake news, social networks, network diffusion, Agent Based Modelling

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1 Introduction

The rapid growth of social media has revolutionized our methods of communication and information sharing. Social media platforms have simplified the process of connecting with people and accessing a wealth of information across various subjects. Nevertheless, this newfound ease of access has also paved the way for the rampant spread of misinformation, which refers to deliberately or unintentionally disseminated false or deceptive information.

The spread of misinformation on social networks is a growing concern, with serious consequences for individuals, communities, and societies. The rampant proliferation of digital misinformation has reached such alarming levels that the World Economic Forum (Tedeneke, 2018) classifies it as one of the primary threats to human society. The sheer magnitude and speed of fake news and misinformation sharing are impacting democratic processes. False news can lead to the improper allocation of resources during terrorist attacks and natural disasters, the misdirection of business investments, and can mislead elections (Vosoughi et al., 2018).

The research focus on the fake news phenomenon intensified following the prominent role of fake news factories during the 2016 US presidential election, as extensively reported (Bovet & Makse, 2019). Fresh theories regarding the dynamics of fake news dissemination have emerged, primarily derived from the analysis of historical media publications, tweets, and posts on social networks and blogs (Pei & Makse, 2013; Zheng et al., 2018). Nonetheless, research into the psychological mechanisms that influence the spread of fake news by individuals, including cognitive biases, actually began as far back as the 1970s (Haselton et al., 2015).

This contribution reviews a selection of research on the factors that contribute to the spread of misinformation, with focus on research utilizing agent-based modeling (ABM) and network modeling to study this phenomenon and presents the state of our ongoing research project in this field.

2 Review of Research

2.1 Social influence

Research by Bond et al. (Bond et al., 2012) shows that results the relationship to the source of political mobilization messages directly influenced political self-expression, information seeking and real world voting behaviour of millions of people. Furthermore, the messages not only influenced the users who received them but also the users' friends, and friends of friends. According to the authors, strong ties are instrumental for spreading both online and real-world behaviour in human social network. A method for quantitatively measuring social influence in mobile social networks is presented by (Peng et al., 2017). Authors propose an evaluation model on social influence by using information entropy to reveal the relationship between social interactions and the strength of social influence. Aston (Aston, 2022) has analysed 2018 Twitter data to study the broader tendencies in collective cognition that compels individuals to spread misinformation. Their conclusion was that those that spread misinformation were highly sensitive to social reward.

2.2 Cognitive Biases

Personal traits, such as cognitive ability (Ahmed & Tan, 2022) and cognitive biases, e.g. confirmation bias, motivated reasoning, and the illusion of validity, can lead individuals to interpret information in a way that confirms their existing beliefs, making them more susceptible to misinformation. This can lead individuals to dismiss contradictory evidence and accept misinformation that aligns with their preconceived notions. Individuals with strong political beliefs, i.e. partisans are particularly more likely to consume and share misinformation that confirms their existing worldview. Concepcion and Sy (Concepcion & Sy, 2023) present a rumor propagation model based on epidemiological models, which incorporates the cognitive process of users when encountering false news, the platform in which the false news spreads, and the relationship of false news with online users. Their results showed that Confirmation Bias, Sharing of Posts, and Algorithmic Ranking are the three main factors affecting the spread of fake news. Geschke et al. (Geschke et al., 2019) have also demonstrated that cognitive biases lead to the formation of echo chambers (see also 2.4).

2.3 Polarization and Echo Chambers

Social media algorithms, which prioritize content based on user engagement, tend to favor information that aligns with users' existing beliefs, leading to the creation of echo chambers. Within these echo chambers, individuals are exposed primarily to information that confirms their existing worldview, reinforcing their biases, resulting in group polarization, and making them more susceptible to misinformation. Fränken and Pilditch (Fränken & Pilditch, 2021) report that positive credibility perceptions of a communicating source can facilitate the growth of a single cascade to produce echo chambers. Similar results are reported by Sasahara et al. (Sasahara et al., 2021), where even with minimal amounts of influence and unfriending, the social network rapidly devolves into segregated, homogeneous communities. Del Vicario et al. (Del Vicario et al., 2016) have demonstrated that information related to distinct narratives such as conspiracy theories and scientific news generates homogeneous and polarized communities (i.e., echo chambers) having similar information consumption patterns. They further show that homogeneity and polarization are the main determinants for predicting the size of information cascades. Garimela et al. (Garimella et al., 2018) have studied the phenomenon of political echo chambers on social media and attempted to identify the users in one of two roles within an echo chamber: partisans and gatekeepers, from social and content features. Geschke et al. (Geschke et al., 2019) have demonstrated that echo chambers emerge due to cognitive mechanisms, such as confirmation bias, under conditions of central information propagation through channels reaching a large part of the population. When social and technological filtering mechanisms were added to the model, polarization of society into even more distinct and less interconnected echo chambers was observed. Echo chambers and the resulting polarization are visualized in Figure 1, showing two distinct communities, where most nodes have connections only within their (echo chamber) community, while the connections between the communities are weak.

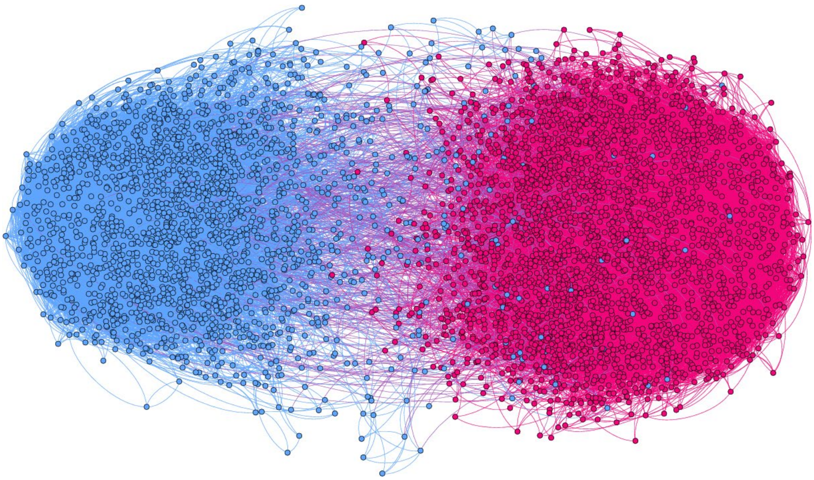

Figure 1: A representation of an echo chamber
Source: (Sasahara et al., 2021)

2.4 Covid-19 Infodemic

The global epidemic of coronavirus (COVID-19) has been almost immediately followed by a global infodemic of misinformation on the source of the virus, virus spread containment methods, treatments and eventually the vaccines. This misinformation originated from social media accounts and websites with no credible evidence to support their claims (Mian & Khan, 2020). The spread of misinformation was fostered by uncritical and uninformed dissemination of misinformation by influential users of social networks (Harff et al., 2022; Shrivastava et al., 2020; Wasike, 2022), including the then US president Donald Trump. Kauk et al. (Kauk et al., 2021) demonstrated a novel approach to characterize the propagation of conspiracy theories through social networks by applying epidemiological models to Twitter data. Author have presented three extended SIR models which include deletion of tweets, fact-checking and both countermeasures combined.

2.5 Russia and War in Ukraine

European Digital Media Observatory task force on Ukraine has detected that approximately 30% of Twitter accounts spreading pro-Russian information within the EU since the beggining of the war on Ukraine are very likely to be bots (Blasi &

Javadi, Mahmoud, 2022). EDMO's survey of the detected pro-Russian accounts shows that 73% of the analyzed accounts produced their first tweet after the start the Russian invasion, suggesting they might be accounts created or activated specifically for the purpose of supporting the Russian narrative on the war in Ukraine. EDMO's reccomendations for tackling the fake news epidemic include the call to "Build an EU-wide pipeline of researchers, university centers, journalists, fact-checkers and other civil society groups with the necessary technical, linguistic and subject-matter knowledge to respond quickly to future information challenges."

The presence of pro-Russian bots on social media, and on Twitter in particular, is however not a new phenomenon. Polarized onlice communities are fertile ground for misinformation operations such as the one Russia conducted to influence the 2016 US election. Instead of trying to force their messages into the mainstream, actors such as the Internet Research Agency (DiResta et al., 2019; Howard et al., 2019) target polarized communities and embed fake accounts within them. Polarized, emotional messages gain traction in an existing echo chamber easier than in a neutral, non-polarized community. Once the influence of fake accounts has been established, they can introduce new viewpoints and amplify divisive and inflammatory narratives that are already circulating.

Figure 2: An example of a meme by the Internet Research Agency that spreads misinformation

Source: (DiResta et al., 2019)

2.6 Artificial Intelligence in Production and Detection of Fake News

The field of Artificial Intelligence (AI) has gained tremendous attention in the last few years due to the proliferation of deep learning models, first in the development of autonomous vehicles, and recently in the field of language models such as ChatGPT. However, AI has been used to develop fakes news detection methods much earlier. An overview of AI related methods with focus on Machine Learning (ML) used in fake news detection is provided in (Khan et al., 2021). Large language models (LLM) have polarized the scientific and educational community, as they promise to automate several aspects of writing, as well as plagiarism. However, a bigger societal danger of LLMs may be their use in the generation of misinformation. Chen and Shu (Chen & Shu, 2023) present a taxonomy of LLM-generated misinformation and categorize and validate the potential real-world methods for generating misinformation with LLMs. Their findings are worrying: LLMs can be instructed to generate misinformation in different types, domains, and errors; LLM-generated misinformation can be harder for humans and misinformation detectors to detect, making it both easier to produce and more dangerous.

3 State of ongoing research project

In this section we present the current state of the simulation model from the ongoing research project »Modelling the influence of individuals' and network characteristics on dissemination of fake news in a social network).« An social network is modelled from the aspect of an agent in the news dissemination process, and its decision-making model is to integrate representations of the relevant cognitive biases. The model allows us to vary the agent behaviour parameters, news generation and processing parameters as well as agent network type and layout in order to examine the influence of these parameters on the dynamics of message diffusion as well as visualize the diffusion of messages through the network. We have so far noticed that the increased frequency of messages can produce non-linear behaviour through network congestion. Currently we are implementing several ideas on the influence of network neighbourghood (three degrees of influence) and the mental well-being of the agent (e.g. generalized anxiety level) on the emergence of polarization.

The simulation interface with animation of agent communication is shown in Figure 3.

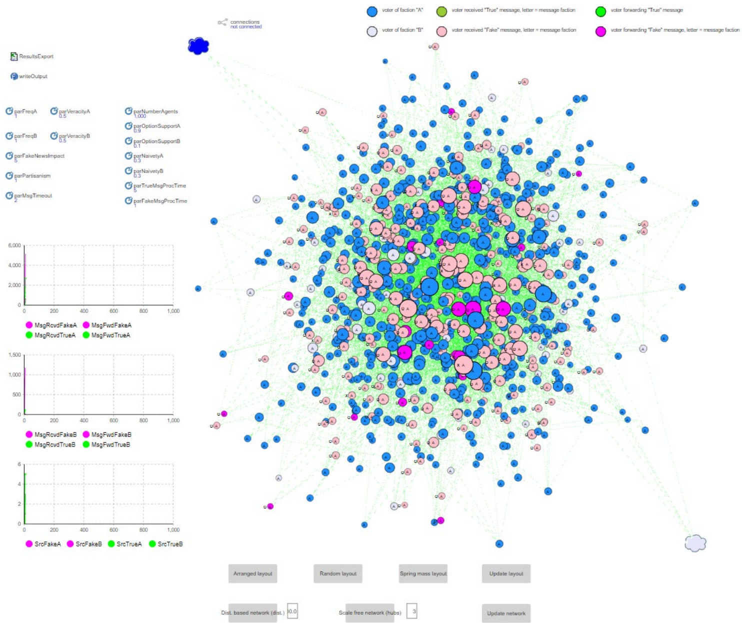

Figure 3: Simulation interface within the current model prototype

Source: own

4 Conclusion

We can summarize our review of research on the diffusion of misinformation in social networks in the following points:

- Misinformation can have a significant impact on individuals' beliefs, attitudes, and behaviors.
- Network structure plays a significant role in the spread of misinformation. Networks with high clustering and low average path length are more susceptible to misinformation outbreaks.
- Several factors lead to the creation of echo chambers, which accelerate polarization:
    - social media algorithms, which create filter bubbles;
    - homophily, the tendency for individuals to connect with others who share similar beliefs and interests;
    - cognitive biases, such as confirmation bias or motivated reasoning, further homophily;

    - social reinforcement, i.e. the fact that individuals are more likely to adopt or share information that has been shared by "close friends", even if they have not independently verified its accuracy, can also create positive feedback loops, resulting in echo chambers that make it difficult to control the spread of misinformation.
- Trust in traditional media outlets and other sources of information can influence an individual's willingness to believe and share misinformation. When individuals lack trust in these sources, they may be more likely to turn to less credible sources for information, increasing their risk of encountering misinformation.
- The rapid pace of information consumption: There is so much information being shared online that it can be difficult to keep up with it all. This can lead to people not taking the time to verify the accuracy of information before they share it.
- Demographics: Certain demographic factors, such as age, education, and socioeconomic status, have been associated with differences in susceptibility to misinformation. For example, older adults and individuals with lower levels of education are more likely to believe in misinformation. (Lewandowsky et al., 2017)
- Media literacy: Media literacy refers to an individual's ability to critically evaluate information and identify misinformation. Individuals with higher levels of media literacy are better equipped to discern credible sources from misinformation.
- Counteracting misinformation requires a multi-pronged approach that includes promoting the availability of credible information, educating individuals about the dangers of misinformation, and developing algorithms to detect and remove false information from social media platforms.

Individuals as well as corporate and government actors exploit a range of network structure related and psychological factors to promote disinformation and drown out facts in social networks. Understanding these factors is crucial for developing effective strategies to combat the spread of misinformation and promote informed decision-making in the digital age.

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