Modelling Misinformation Spread: The Role of Network Density in Diverse Social Structures

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Abstract. Understanding the relationship between network features and misinformation propagation is crucial for mitigating the spread of false information. This study examines how network density affects the dissemination of hoax news using an SIR (Susceptible-Infectious-Recovered) framework. Our findings show that increased network density leads to more believers in misinformation, with the number of believers rising higher among more gullible individuals. In segregated networks, denser clusters have a higher proportion of believers, regardless of group gullibility parity. As an important result, a dense minority can significantly amplify belief percentages within majority groups, highlighting the substantial impact of minority structure on majority dynamics.

Keywords: Misinformation, Network Density, Agent-Based Model, Network Segregation, Minority Effect

1 Introduction

Misinformation poses a significant challenge in today's digitized society [1–3], with social media platforms often serving as prime vectors for its dissemination, fueling polarisation [4], anti-vax sentiments [5], violence [6, 7], and political interference [8, 9]. Despite its pervasive effects, our understanding of the mechanisms underlying misinformation remains elusive [10]. In particular, we still do not fully understand the role of social groups (and their structure) in misinformation spreading. In this work, we investigate the dynamics of misinformation spread, focusing on the role of network density in diverse social structures.

Previous works have highlighted the main role of network structure in amplifying falsehoods and the need for a better understanding of group density [11–13]. For example, higher social network density is linked to higher dissemination of misinformation, particularly within conservative clusters [11]. Similarly, conservative Twitter users often inhabit denser networks and are more exposed to low-credibility content, perpetuating the circulation of partisan content [12]. Such homogeneous social networks foster an environment conducive to misinformation proliferation, making individuals more susceptible to misinformation and triggering cascade effects that extend to the broader population [13].

To understand these dynamics, simulation provides a valuable framework to gain insights into real-world phenomena and pinpoint influential factors [14]. For instance, Tambuscio et al. proposed a model that simulates individuals transitioning among susceptible, fact-checker, and believer states, shedding light on the mechanisms driving misinformation propagation and guiding counter-strategies [15]. However, their model focuses primarily on individual traits, such as gullibility, without accounting for the impact of network density [16].

In our work, we highlight the fundamental role of network density in both segregated and non-segregated networks. We explore how denser networks correlate with a higher percentage of believers in hoaxes and investigate the impact of a dense minority on the belief percentage within the majority. Our results unveils a positive correlation between network density and the prevalence of *believers*—individuals propagating misinformation—within a network. This correlation echoes findings from prior empirical studies [17, 18, 12] and suggests that denser networks facilitate heightened misinformation dissemination. This trend persists within segregated networks, where increased density within groups corresponds to a greater number of believers within those groups.

We also explore cross-group effects and reveal that in networks with both majority and minority groups, the majority influences the minority, as expected. Surprisingly, however, we uncover a reciprocal effect: changing the density of the minority group—while keeping the majority's density constant—affects the majority as well.

These insights carry significant implications for mitigating and addressing misinformation [19], emphasizing the critical role of our social connections. They demonstrate that actions from even highly segregated groups can influence the broader population, shaping collective behaviour. The interplay between these findings and the impact of superspreaders remains an open question [20].

2 Modelling misinformation spread

To understand the effect of density on the network, we model misinformation spread using an SIR framework. We apply this model to networks of different densities in segregated and unsegregated networks.

2.1 Tambuscio's model

We use Tambuscio's misinformation spread model, tailored for analyzing hoax dissemination in social networks [15] (see Figure 1). This model, rooted in epidemic modelling, treats hoaxes as viral infections and integrates a mechanism for fact-checking to combat their propagation. The dynamics of the model are governed by the interactions between individuals with their neighbours in different states and the probabilities associated with the model's parameters.

In the model, individuals in the network can be in one of three states: susceptible (S), believer (B), or fact-checker (F). Susceptible individuals have not been exposed to the hoax or have forgotten about it, whereas believers have been exposed to the hoax and believe it. Finally, fact-checkers have verified the hoax and no longer believe it.

The model is characterized by four parameters: the overall spreading rate β, the agents' gullibility α, the probability p_{verify} to verify a hoax (i.e., the probability that a believer will fact-check a hoax and become a fact-checker), and the probability p_{forget} that an individual will forget their current belief state and become susceptible again.

The spread of a hoax and its debunking can be described as follows:

1. Spread of the Hoax: When a susceptible individual comes into contact with a believer, they may become infected with the hoax and the probability of that is equal to:

$$f_i(t) = \beta \frac{n_i^B(t)(1+\alpha)}{n_i^B(t)(1+\alpha) + n_i^F(t)(1-\alpha)}, \tag{1}$$

   for the i-th agent at time step t, where $n_i^B(t)$ and $n_i^F(t)$ represent the number of its neighbors in states B and F, respectively.

2. Fact-checking and Debunking: Believers have a chance to fact-check the hoax and become fact-checkers. This transition from state B to F is governed by p_{verify}, whereas the transition form S to F is calculated using the following function:

$$g_i(t) = \beta \frac{n_i^F(t)(1-\alpha)}{n_i^B(t)(1+\alpha) + n_i^F(t)(1-\alpha)}. \tag{2}$$

   Once an individual becomes a fact-checker, they no longer spread the hoax but instead spread the debunking information.

3. Forgetting: Both believers and fact-checkers may forget their current belief state over time and revert to a susceptible state. This forgetting process is modeled with a single probability, the probability to forget (p_{forget}), which applies to both believers and fact-checkers.

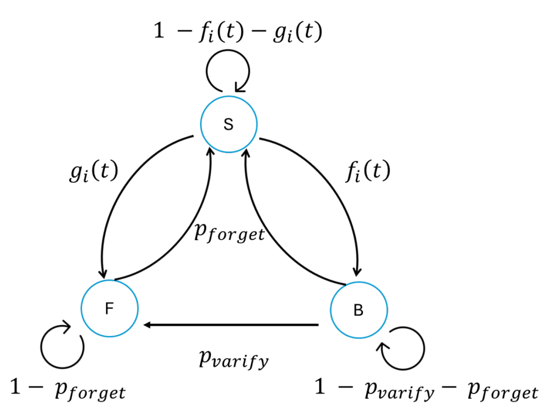


Fig. 1: Tambuscio's model – transitions between states. Adapted from [15].

Let $s_i(t)$ represent the state of the ith agent at time t, and define the state indicator function for $X \in \{B, F, S\}$ as $s^i_X(t) = \delta(s_i(t), X)$. $p_i(t) = (p^i_B(t), p^i_F(t), p^i_S(t))$ describes the probability that node i is in each of the three states at time t.

2.2 Network Generation

To understand the impact of network density on misinformation spread, we use Tambuscio's model to networks with different densities in segregated and unsegregated structures. We generate networks by considering the sizes of minority and majority groups, as well as the densities of intra-group and inter-group connections.

To generate networks, we use the edge probability matrix to independently control the probability of links within and between groups [21]. The edge probability matrix H is defined as follows:

$$H = \begin{bmatrix} h_{00} & h_{01} \\ h_{01} & h_{11} \end{bmatrix}, \tag{3}$$

where h_{ii} is the probability of an edge between two nodes of the same group, whereas h_{01} is the probability of creating an edge between nodes from different groups. In our work, we denote f_0 as the proportion of nodes belonging to the minority group.

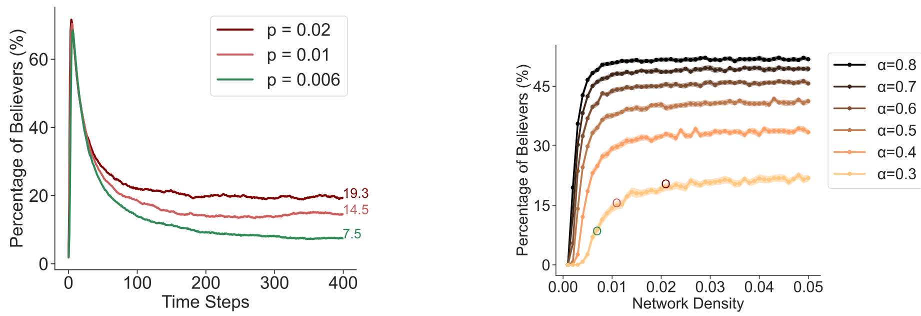
3 Results

We analyze both unsegregated and segregated networks. In unsegregated networks, our results show that denser networks lead to more believers in hoaxes. For segregated networks, increasing the density of the minority group not only increases the percentage of believers within that group but also affects the majority group, especially as the minority size grows.

3.1 Unsegregated Networks

Figure 2a illustrates the impact of network density on the percentage of believers with the same level of gullibility ($\alpha = 0.3$) across different values of the parameter p. The parameter p determines the probability of links between nodes in an Erdős-Rényi (ER) network. As the value of p increases, indicating higher network density, the percentage of individuals endorsing the misinformation also increases. This trend underscores the role of network density in facilitating the spread of misinformation, highlighting the importance of understanding network structure in combating false beliefs.

Figure 2b presents the final percentages of believers in a network comprising 1000 nodes, with varying values of the parameter p and gullibility (α). Each line in the plot represents a different level of gullibility, indicating how belief



(a) (b)

Fig. 2: a) Percentage of Believers over time ($\alpha = 0.3$). b) Effect of Network Density on Percentage of Believers ($n = 1000$, iterations $= 50$, $p_{\text{verify}} = 0.05$, $p_{\text{forget}} = 0.1$, $\beta = 0.5$).

formation is influenced by both network density and individual susceptibility. Across all lines representing different levels of gullibility, an increase in p corresponds to a higher percentage of believers. As p increases, indicating higher network density, the percentage of individuals endorsing the misinformation also increases.

3.2 Segregated Networks

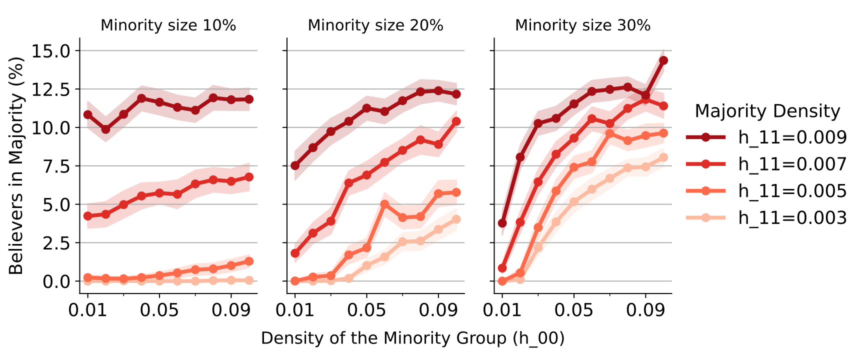


Fig. 3: Percentage of Believers in the Majority for Different Minority Network Densities ($n = 1000$, $h_{01} = 0.002$, steps $= 1000$, iterations $= 100$, $p_{\text{verify}} = 0.05$, $p_{\text{forget}} = 0.1$, $\beta = 0.5$, $\alpha = 0.3$)

Figure 3 presents line charts illustrating the average percentage of believer members in the majority group across varying minority group sizes, ranging from

10% to 30% of the total population. Each line plot represents the influence of minority group density on belief formation dynamics.

The x-axis determines the minority density and the y-axis is the percentage of believer members in the majority group. The density of the majority group is controlled by the h_{11} parameter. Consistent with the results of unsegregated networks, an increase in the density of the majority group is expected to correlate with a higher percentage of believers within this group.

An intriguing observation is the amplification effect of increasing the density of the minority group on the percentage of believers in the majority group. Additionally, the effect of the dense minority group on belief formation increases with its size.

For example, with $h_{11} = 0.007$ and a minority group comprising 20% of the population, increasing the density of the minority group results in a five-fold increase in believers within the majority group, from around 2% to 10%.

4 Discussion

Our findings underscore the significant impact of network density on the spread of misinformation. Higher density in unsegregated and segregated networks leads to a greater prevalence of false beliefs. The presence of a dense minority group further amplifies this effect within the majority group. These insights highlight the importance of understanding network structure to develop effective strategies for combating misinformation.

Our results suggest that focusing on dense communities should be prioritized in order to fight the spread of misinformation. These communities are not only highly suitable for the diffusion of misinformation but also amplify the percentage of believers in hoax news within the broader population. By targeting these dense clusters, interventions can be more effective in reducing the overall impact of misinformation.

Furthermore, our results serve as a warning even for individuals with low gullibility: they may find themselves trapped in dense communities, inadvertently playing a role in spreading misinformation. Despite their skepticism, the high frequency of interactions within these networks increases the likelihood that they encounter and share false information.

This study advances our understanding of how network density influences belief formation and misinformation spread. By elucidating these dynamics, we can inform targeted interventions to promote critical thinking and enhance resilience against misinformation. Future research should explore additional network configurations and real-world applications of these findings to further mitigate the harmful effects of misinformation.

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