An Experimental Evaluation of Social Pressure in Opinion Dynamics Models

Stamo Avgoustatou
Department of Digital Media and Communication
Ionian University, Argostoli, Greece
saugoustatou@ionio.gr

Dimitris Ampeliotis
Department of Digital Media and Communication
Ionian University, Argostoli, Greece
ampeliotis@ionio.gr

***Abstract*—We study a recently proposed model for opinion dynamics that takes into account social pressure, that is, the fact that agents are reluctant to reveal their actual opinions in an environment where other agents may have different views. In the examined model, each agent has an inherent opinion that represents their actual views, while agents may choose to declare an opinion that is different from their inherent one when they sense that they are in an environment where neighboring agents do not agree with their inherent opinion. At any point in time, agents communicate their stated views within the network which depend on the social pressure they receive within the network as well as their inherent views. Nodes tend to conform to the views of other nodes in the network. We perform numerical experiments using this model and several types of graphs that are commonly used to represent social networks. Our scope is to measure the strength of social pressure in various scenarios, by demonstrating the *honesty percentage*, i.e., the percentage of agents that declare their true inherent opinion, as a function of time. The numerical results produced show that the type of network significantly affects the characteristics of the social pressure.**

I. Introduction

Opinion dynamics is a field of research that studies how individuals' opinions evolve through social interactions. This happens as people exchange opinions about anything on a daily basis. This field uses mathematical and physical models, as well as computational tools, especially agent-based models, to investigate the spread and evolution of opinions in a set. Agents can be either single individuals or even sets of individuals [1]. The study of opinion dynamics has engaged many disciplines and includes fields such as sociology, psychology, economics, mathematics, physics, computer science, statistics and control theory. The beginning was after 1960 when sociologists and psychologists started to deal with this issue [2]. In social networks, opinion dynamics refers to the study of how individuals' opinions are formed and how they evolve during their interaction with other individuals in the network. This includes analyzing how opinions are propagated, how they are influenced by the structure of the network and how they can lead to phenomena such as polarization or consensus. In general, consensus in real life is very difficult as many things play a role in changing the views of nodes over time [3]. Experiments in the field of psychology have shown that individuals often conform to the views of their peers in order to be accepted by the group, even if those views do not align with their actual views on an issue [4][5][6][7][8].

This research was funded and conducted in the framework of the M.Sc. program "New Media Communication and Digital Marketing" offered by the Department of Digital Media and Communication of the Ionian University.

Overall, the study of opinion dynamics offers valuable insights into how opinions are formed, evolve and spread in social networks, contributing to understanding and addressing contemporary social challenges.

In this work we study the notion of "social pressure", which refers to the tendency of individuals to adjust their expressed views to align with the views of their neighbors in a social network. In recent literature, the term "social pressure" has been examined in several studies that analyze the dynamics of opinions under the influence of different opinions. For example, [9] studies the behavior of individuals' stated opinions in social networks under social pressure using the Pólya urn interaction model. In addition, the article [10] proposes a new model of opinion dynamics to study how differences between private and expressed opinions arise in social networks, taking into account social pressure. These studies provide further understanding of how social pressure affects the formation and evolution of opinions in social networks.

The scope of this work is to try to quantify the strength of social pressure, by performing numerical experiments using the model of [11] and several network / graph models that are commonly used to represent social networks. To this end, we introduce the notion of *honesty percentage*, that is, the percentage of agents that declare their true, inherent opinions when the network has converged. Thus, when the honesty percentage has high values, the strength of the social pressure is limited, as the nodes express their true beliefs.

II. Pleriminaries

A. Basic algorithms/models for opinion dynamics

The Degroot is an opinion model for social network analysis and is named after its creator Morris Degroot in 1974 [12]. Agents update their opinions by taking a weighted average of the opinions of their neighbours. Using the theory of Markov chains, it can be shown that the model leads to consensus, i.e. the views converge to a common value. In real life, absolute consensus is rare. People retain a part of their original opinion and do not fully adopt the views of others. Every day they exchange views on everything but there is rarely complete agreement as consensus is a complex process. The solution came in the Friedkin and Johnsen's model model. In the

Friedkin-Johnsen (FJ) model, each agent also has a personal secret opinion s_i that does not change with time, but affects the opinion expressed by the agent at every moment [13]. In addition, Ye et al. also considered an extension of Friedkin and Johnsen's model, where nodes have private and expressed views, and updated linearly through time [10]. There are also many variations of the above two models in the literature [14].

Another well-known model in the literature is the Hegselmann-Krause (HK) model [15]. It is a classic model of opinion dynamics developed by Hegselmann and Krause in 2002. Each agent updates its viewpoint based on the views of its neighbors, which are those that are at most distant from it within a certain boundary determined by its tolerance (a bound ϵ). Neighbor selection is based on the distance of each agent's view from the node's view, and is determined by the tolerance bound ϵ.

The "Voter Model", one of the first stochastic (probabilistic) models of opinion dynamics. This model considers a set of agents who have binary opinions (e.g., Yes/No). At each point in time, an individual is randomly selected and decides whether to change his/her opinion. The probability of changing depends on the opinions of its neighbors. The Voter Model and its variants are used to study how opinions evolve in social networks based on stochastic processes. Their results are useful in sociology, physics and data science. At each time step, a node i is randomly selected along with a node in its neighborhood and the node receives the opinion of its neighbor. If the agent i has the opinion $X_i(t)$ at the time t and has randomly selected the node j, the opinion $x_i(t+1)$ will be $x_i(t+1) = x_j(t)$ [16]. Another stochastic model in which the values of the opinions, unlike the voter, are not discrete but continuous is the Deffuant - Weisbuch (DW) model. At each time step, two randomly selected individuals compare their opinions. If the difference of their views is less than a confidence threshold ϵ, then they move compromisingly closer to each other according to a learning rate μ (learning rate). If the difference is greater than ϵ, they do not interact. DW is a serial model, since at each time t only two agents,i and j, interact and possibly update their opinion. Although very difficult there is a possibility that an agent may never update its opinion, having similar behavior to a stubborn node, which never updates its opinion. The model according to research always converges, where this means that no matter how different people's initial opinions are or how selective they are in whom they interact with, the system always reaches a stable state [17], [18], [19]. Studies in opinion dynamics models where nodes have both expressed and private opinions are very important as large differences between the two within the literature are seen to create dissatisfaction and tension that can lead to violent and unpredictable actions [20]. Hayhoe et al. proposed a model that simulates how an epidemic or an opinion spreads in a network, taking into account both the individual history of nodes and the influence of their neighbours. It uses the mechanism of Pólya urns to describe the amplification of a state and the probabilities of spreading within the network [21].

In all the models already mentioned, nodes are assumed to share their opinion with their neighbors honestly. More recently, models that do not make this assumption have appeared [22], [9], [11]. In that model, nodes have two kinds of opinions, the intrinsic one which they do not express, and the expressed opinion which they share with their neighbors, that may be different from what they actually believe. The model utilizes discrete choice models from social choice theory and how they relate to the dynamics of opinion diffusion using an interactive Pólya urn model. Discrete choice models try to explain how people choose between multiple alternatives. In particular, according to the classical BTL (Bradley-Terry-Luce [23]) model, if we have n options with n respective preference parameters $\alpha_1, \alpha_2, ..., \alpha_n$, then the probability of choosing the i-th option is given by

$$P_i = \frac{\alpha_i}{\alpha_1 + \alpha_2 + ...\alpha_n} \ . \tag{1}$$

Each agent has an intrinsic preference for a viewpoint. The probability of considering a view as "true" is proportional to the number of times he has observed it being transmitted. This is related to the Pólya urn model, where reinforcing a view increases the probability that it will be adopted again in the future. The BTL model describes how people choose between different views based on perceived preference or frequency of observation. This model also explains viewpoint diffusion, as people tend to adopt and express views that they hear more frequently from their environment. More details about this model are given in Section III.B.

B. Basic network models

In opinion dynamics problems, various network models are used to describe the interactions between individuals and the spread of opinions. Some of the basic models are:

1) Random Networks: These networks are based on the Erdős-Rényi (ER) model, where edges between nodes are randomly generated with some probability. They are used to analyze unstructured social interactions and are a good approach for networks where connections are independent and random. In the Erdős-Rényi model (also known as the random graph model), the nodes of the network are randomly connected with a certain probability. In the literature there are several studies of opinion dynamics problems that consider this type of networks [24], [25], [26], [27], [28].

2) Random Geometrical Graph: RGGs are random graphs where nodes are randomly placed in a two-dimensional or multidimensional space and connected if their distance is less than a threshold. They represent social networks with geographical constraints (e.g., communication in physical spaces, wireless networks, smart cities); based on geographical proximity. They are used to study the spread of opinions in physical communities, where proximity plays a role in creating social ties. They are often associated with the Deffuant-Weisbuch model, where nodes interact if their difference in views is less than some threshold. The are useful for modeling local interactions where physical distance plays a role. Random Geometric Graphs are important in opinion dynamics, especially for problems involving geographical constraints and local interactions. Within the literature we find such graphs for the case study of opinion dynamics problems, [29], [30], [31].

3) Small-World Networks: They are usually based on the Watts-Strogatz model describing networks that combine features of regular networks and random networks. They model social networks where most people have local connections and some distant connections. It is suitable for spreading opinions through social circles and random connections. Small-world networks are characterized by the fact that the majority of nodes are connected to each other through very short paths, but with a high degree of local coherence. We also find studies within the literature on such networks for opinion dynamics problems, [32], [33], [34].

4) Scale-Free Network: Usually these networks are based on the Barabási-Albert (BA) model, where nodes follow a power law degree distribution. Some hubs have many connections and significantly influence the spread of opinions. It models social networks where a few hubs have many connections and most hubs have few connections. These networks are mainly suitable for studying the influence of individuals with large networks (e.g. influencers, opinion leaders). Opinions spread through these hubs much faster than in random networks. It is a type of network often used in the literature for opinion dynamics studies [35], [26], [36].

5) Networks with community Structure: In networks with community structure, nodes are organized into communities with many internal and few external connections. They are extremely useful in the study of opinion propagation, as they represent groups of people with strong internal ties and weaker connections to other communities. Networks with community structure play a crucial role in opinion dynamics, as they determine how opinions spread or remain static within social groups. They are particularly useful for studying polarization and opinion diffusion between communities. Several studies have considered these network models for the study of opinion dynamics, [37], [38], [39].

III. Opinion Dynamics Under Social Pressure

A. The Relationship between Social Pressure and Opinion Dynamics

In opinion dynamics models, social pressure determines how opinions are formed and changed within social networks. In the Deffuant-Weisbuch model, individuals change opinion only if the difference between them is below a certain threshold. Social pressure here determines whether and how much one will adapt. In the Hegselmann-Krause model [15] individuals are influenced by everyone within a certain perception radius, showing that social pressure comes from their social environment. In the Friedkin-Johnsen model we see how social influence leads to the formation of collective views, depending on the strength of social pressure. Social pressure is something that can potentially reverse the evolution of views in a network. It has been shown that individuals may accept false information due to the pressure of their social environment [40]. Social pressure can also create cohesion in groups, but it can also reinforce divisions in society [41]. Also the social pressure resulting from the perception of social norms can influence the behaviour of individuals and promote positive social changes [42].

B. A model of opinion dynamics under social pressure

In this paragraph we briefly describe the opinion dynamics model that was proposed in [11], that takes into account social pressure, which is the subject of study in our work. We consider a set of N nodes that are connected via some network / graph. The opinions of the nodes can take the values 0 or 1. Each node $v \in V$ where $V = \{1, \dots, N\}$, has an inherent opinion $\varphi_v \in \{0, 1\}$. At discrete time $n \in \mathbb{Z}^+$, each agent v expresses a declared opinion $\psi_{v,n} \in \{0, 1\}$ according to the formula

$$\psi_{v,n} \triangleq \begin{cases} \varphi_v, & \text{with probability } p_{v,n}, \\ 1 - \varphi_v, & \text{with probability } 1 - p_{v,n}. \end{cases} \quad (2)$$

According to Equation (2), agent v declares its inherent opinion with probability $p_{v,n} \in (0, 1)$, or expresses the opposite opinion with probability $1 - p_{v,n}$. In this model, the expressed view of a node is visible to all neighboring nodes according to the communication graph considered.

According to the model, the probability $p_{v,n}$ with which the agent expresses their true opinion, is also time varying. In more detail, it is given by the BTL model that expresses the probability that one person/object is chosen over another, based on some ”weight”. Each agent has two parameters $a_{v,n}$ and $b_{v,n}$, which are updated over time and represent the ”reinforcement” in favor of truth or falsehood. The probability of expressing the true opinion is given by

$$p_{v,n} \triangleq \frac{\alpha_{v,n}}{\alpha_{v,n} + \beta_{v,n}} \ , \quad (3)$$

where the parameters $a_{v,n}$ and $b_{v,n} \in \mathbb{R}^+$ are updated as follows:

1) For $n = 0$, $a_{v,0} = b_{v,0} = 1$ for all $v \in V$, to simplify the results, however, they can take any positive values
2) For $n \geq 1$, every agent $v \in V$ observes its neighbors' declared opinions $\{\psi_{u,n-1} : u \in \mathcal{N}_v\}$, where $\mathcal{N}_v = \{u \in V : \{v, u\} \in E\}$ denotes its set of neighbors. The random parameters $a_{v,n}$ and $b_{v,n}$ are given by the following update equations.

$$a_{v,n} = a_{v,n-1} + \gamma \sum_{u \in \mathcal{N}_v} 1\{\psi_{u,n-1} = \varphi_v\} \quad (4)$$

$$b_{v,n} = b_{v,n-1} + \sum_{u \in \mathcal{N}_v} 1\{\psi_{u,n-1} \neq \varphi_v\} \quad (5)$$

where $\gamma \in \mathbb{R}^+$ is a known honesty parameter, that controls the tendency of agents to express their true opinions. Also, $1\{\cdot\}$ denotes an indicator function that takes the value 1 when its argument is true, and 0 otherwise.

IV. Numerical Results

To analyze the model of opinion dynamics under social pressure, simulations were performed for several different types of networks using the MATLAB environment. Specifically, the following four types of networks were considered:

- Complete graph
- Random graph / Erdős – Rényi graph (0.2 connection probability)
- Scale-Free Network (Barabási–Albert)

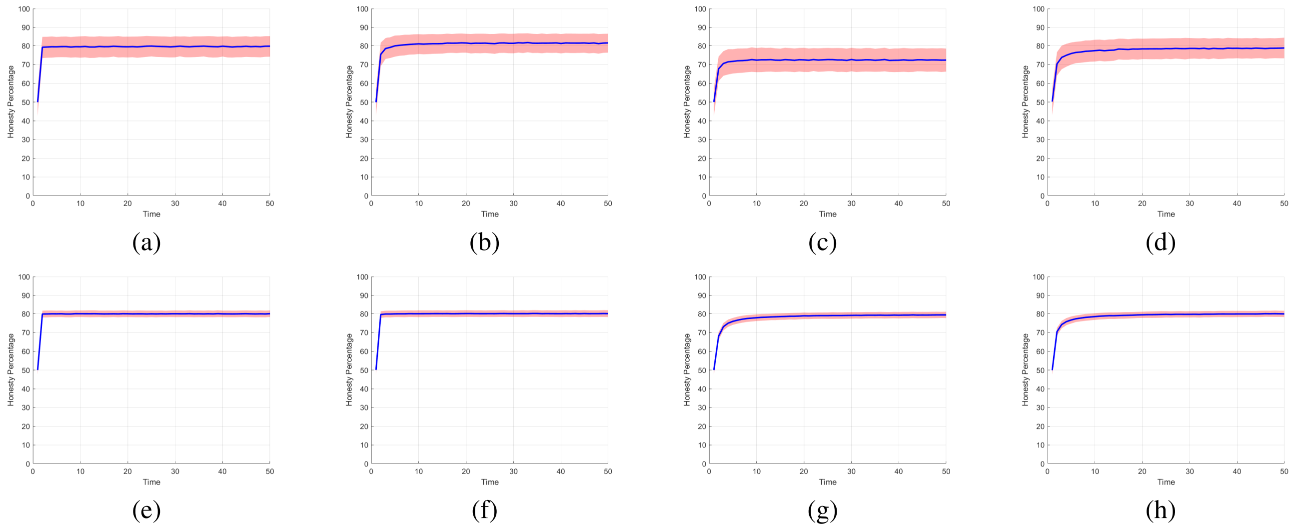

Fig. 1. Honesty percentage as a function of time, with $\pm\sigma$ intervals, for several types of graphs: (a) Complete graph with 50 nodes, (b) Random graph (0.2 connection probability) with 50 nodes, (c) Scale free (Barabási–Albert) graph with 50 nodes, (d) Small world (Watts–Strogatz) graph with 50 nodes, (e) Complete graph with 500 nodes, (f) Random graph (0.2 connection probability) with 500 nodes, (g) Scale free (Barabási–Albert) graph with 500 nodes, (h) Small world (Watts–Strogatz) graph with 500 nodes.

- Small-World Network (Watts–Strogatz)

The simulations were performed for two different network sizes, namely 50 and 500 nodes. The honesty factor γ was set equal to the value 4, thus considering nodes with a tendency to be relatively honest. Also, each simulation was repeated $2,000$ times, where in each case different inherent opinions were used, randomly selected in $\{0, 1\}$ with equal probabilities. The total simulation time was set equal to 50 time steps. The networks / graphs considered were constant across each run.

In Figure 1, we demonstrate the honesty percentage as a function of time, for each one of the considered cases (2 network sizes, 4 types of networks). The plots also demonstrate the $\pm\sigma$ intervals for the honesty percentage at each time instant. By careful inspection of the results in Figure 1, the most important observations are the following:

Strength of social pressure: Looking at the plots of Figure 1, we observe that the final values of the honesty percentage are smaller for scale-free and small-world networks, as compared to the respective values for complete and random graphs. This is true for both small and larger networks. This implies that the strength of social pressure is greater for scale-free and small-world networks. In other words, networks that are comprised of strongly connected communities impose stronger social pressure, as individuals with different opinions cannot easily express their inherent views.

Convergence time: We also notice from the results of Figure 1 that random and complete graphs stabilize faster. This can be justified as high and uniform connectivity results in fast information propagation. In a complete graph, every node in the network is connected to all other nodes in the network. Therefore, each node receives influence from the whole network simultaneously, and this results in a faster convergence towards a constant honesty percentage. In random graphs, the connections are random, which means that information spreads uniformly and quite fast, although not as fast as in complete graphs. In both of these types of graphs, all agents are affected almost equally by the network leading to a steady state much faster. In small world and scale free networks, the influence is unevenly distributed as hubs (nodes with many connections) have disproportionate influence, resulting in slower convergence within the network.

Less variation in larger networks: It is evident from the plots of Figure 1 that larger networks (bottom row, 500 nodes) result in less variation of the honesty percentage, as compared to smaller networks (top row, 50 nodes), for all time instants. This implies that the strength of social pressure may differ more significantly in smaller networks.

V. Conclusion

In this work, we studied a recently proposed model of opinion dynamics, that takes into account the notion of social pressure [11]. In particular, our scope was to evaluate the strength of social pressure in a number of network models that are commonly used to represent social networks. We performed numerical experiments and demonstrated the honesty percentage, that is, the percentage of nodes that express their true, inherent opinion to their neighbors. This metric can be viewed as a measure of the strength of social pressure, in the sense that a higher honesty percentage implies weaker influence. Our results indicate that the type of network and its size have a significant impact on strength of social pressure, as well as on the amount of time required for convergence. Future work will focus on a more elaborate experimental evaluation, as well as on approaches to infer information about the inherent opinions of the agents.

References

[1] H. Xia, H. Wang, and Z. Xuan, “Opinion dynamics: A multidisciplinary review and perspective on future research,” *International Journal of Knowledge and Systems Science (IJKSS)*, vol. 2, no. 4, pp. 72–91, 2011.

[2] M. Grabisch and A. Rusinowska, “A survey on nonstrategic models of opinion dynamics,” *Games*, vol. 11, no. 4, p. 65, 2020.

[3] A. F. Peralta, J. Kertész, and G. Iñiguez, "Opinion dynamics in social networks: From models to data," *arXiv preprint arXiv:2201.01322*, 2022.

[4] R. B. Cialdini and N. J. Goldstein, "Social influence: Compliance and conformity," *Annu. Rev. Psychol.*, vol. 55, no. 1, pp. 591–621, 2004.

[5] R. S. Crutchfield, "Conformity and character." *American psychologist*, vol. 10, no. 5, p. 191, 1955.

[6] C. A. Insko, S. Drenan, M. R. Solomon, R. Smith, and T. J. Wade, "Conformity as a function of the consistency of positive self-evaluation with being liked and being right," *Journal of Experimental Social Psychology*, vol. 19, no. 4, pp. 341–358, 1983.

[7] S. E. Asch, "Effects of group pressure upon the modification and distortion of judgments," in *Organizational influence processes*. Routledge, 2016, pp. 295–303.

[8] ——, "Opinions and social pressure," *Scientific American*, vol. 193, no. 5, pp. 31–35, 1955.

[9] J. Tang, A. Adler, A. Ajorlou, and A. Jadbabaie, "Stochastic opinion dynamics under social pressure in arbitrary networks," in *2023 62nd IEEE Conference on Decision and Control (CDC)*. IEEE, 2023, pp. 1360–1366.

[10] M. Ye, Y. Qin, A. Govaert, B. D. Anderson, and M. Cao, "An influence network model to study discrepancies in expressed and private opinions," *Automatica*, vol. 107, pp. 371–381, 2019.

[11] A. Jadbabaie, A. Makur, E. Mossel, and R. Salhab, "Inference in opinion dynamics under social pressure," *IEEE Transactions on Automatic Control*, 2022.

[12] M. H. DeGroot, "Reaching a consensus," *Journal of the American Statistical association*, vol. 69, no. 345, pp. 118–121, 1974.

[13] N. E. Friedkin and E. C. Johnsen, "Social influence and opinions," *Journal of Mathematical Sociology*, vol. 15, no. 3-4, pp. 193–206, 1990.

[14] M. Ye, *Opinion dynamics and the evolution of social power in social networks*. Springer, 2019.

[15] H. Rainer and U. Krause, "Opinion dynamics and bounded confidence: models, analysis and simulation," *Journal of Artificial Societies and Social Simulation*, 2002.

[16] R. A. Holley and T. M. Liggett, "Ergodic theorems for weakly interacting infinite systems and the voter model," *The annals of probability*, pp. 643–663, 1975.

[17] G. Chen, W. Su, W. Mei, and F. Bullo, "Convergence of the heterogeneous deffuant-weisbuch model: A complete proof and some extensions," *IEEE Transactions on Automatic Control*, 2024.

[18] G. Weisbuch, G. Deffuant, F. Amblard, and J.-P. Nadal, "Meet, discuss, and segregate!" *Complexity*, vol. 7, no. 3, pp. 55–63, 2002.

[19] A. Sîrbu, V. Loreto, V. D. Servedio, and F. Tria, "Opinion dynamics: models, extensions and external effects," *Participatory sensing, opinions and collective awareness*, pp. 363–401, 2017.

[20] J. Goodwin, "Why we were surprised (again) by the arab spring," *Swiss Political Science Review*, vol. 17, no. 4, pp. 452–456, 2011.

[21] M. Hayhoe, F. Alajaji, and B. Gharesifard, "A polya contagion model for networks," *IEEE Transactions on Control of Network Systems*, vol. 5, no. 4, pp. 1998–2010, 2017.

[22] K. Ntemos, V. Bordignon, S. Vlaski, and A. H. Sayed, "Social learning under inferential attacks," in *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2021, pp. 5479–5483.

[23] A. Vista, R. Adams, and D. Cloney, "Modelling pairwise comparisons using the bradley–terry–luce (btl) model," 2015.

[24] M. F. Granha, A. L. Vilela, C. Wang, K. P. Nelson, and H. E. Stanley, "Opinion dynamics in financial markets via random networks," *Proceedings of the National Academy of Sciences*, vol. 119, no. 49, p. e2201573119, 2022.

[25] Z. Zhang, W. Xu, Z. Zhang, and G. Chen, "Opinion dynamics incorporating higher-order interactions," in *2020 IEEE International Conference on Data Mining (ICDM)*. IEEE, 2020, pp. 1430–1435.

[26] M. E. Newman, "The structure and function of complex networks," *SIAM review*, vol. 45, no. 2, pp. 167–256, 2003.

[27] M. Drobyshevskiy and D. Turdakov, "Random graph modeling: A survey of the concepts," *ACM computing surveys (CSUR)*, vol. 52, no. 6, pp. 1–36, 2019.

[28] W. Wang, "Opinion dynamics on typical complex networks and applications," Ph.D. dissertation, UCL (University College London), 2017.

[29] W. Zhang, C. C. Lim, G. Korniss, and B. K. Szymanski, "Opinion dynamics and influencing on random geometric graphs," *Scientific reports*, vol. 4, no. 1, p. 5568, 2014.

[30] M. Penrose, *Random geometric graphs*. OUP Oxford, 2003, vol. 5.

[31] J. Dall and M. Christensen, "Random geometric graphs," *Physical review E*, vol. 66, no. 1, p. 016121, 2002.

[32] D. J. Watts, "Networks, dynamics, and the small-world phenomenon," *American Journal of sociology*, vol. 105, no. 2, pp. 493–527, 1999.

[33] V. Dornelas, M. Ramos, and C. Anteneodo, "Impact of network randomness on multiple opinion dynamics," *Physica A: Statistical Mechanics and its Applications*, vol. 506, pp. 197–207, 2018.

[34] I. Kanovsky and O. Yaary, "Model of opinion spreading in social networks," *arXiv preprint arXiv:1106.0872*, 2011.

[35] L. Beauguitte and C. Ducruet, "Scale-free and small-world networks in geographical research: A critical examination," in *17th European Colloquium on Theoretical and Quantitative Geography*, 2011, pp. 663–671.

[36] I. Voitalov, P. Van Der Hoorn, R. Van Der Hofstad, and D. Krioukov, "Scale-free networks well done," *Physical Review Research*, vol. 1, no. 3, p. 033034, 2019.

[37] F. J. Y. Yan, "The effects of similarity and randomness of network on opinion formation," *Journal of Computers*, vol. 27, no. 3, pp. 63–70, 2016.

[38] Y. Xing and K. H. Johansson, "Transient behavior of gossip opinion dynamics with community structure," *Automatica*, vol. 164, p. 111627, 2024.

[39] F. Klingner, "Opinion dynamics on networks with community structure," *Name of Journal*, vol. Volume, no. Number, p. Pages, Year.

[40] S. Vosoughi, D. Roy, and S. Aral, "The spread of true and false news online," *science*, vol. 359, no. 6380, pp. 1146–1151, 2018.

[41] C. A. Bail, L. P. Argyle, T. W. Brown, J. P. Bumpus, H. Chen, M. F. Hunzaker, J. Lee, M. Mann, F. Merhout, and A. Volfovsky, "Exposure to opposing views on social media can increase political polarization," *Proceedings of the National Academy of Sciences*, vol. 115, no. 37, pp. 9216–9221, 2018.

[42] M. E. Tankard and E. L. Paluck, "Norm perception as a vehicle for social change," *Social Issues and Policy Review*, vol. 10, no. 1, pp. 181–211, 2016.