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Original Article

AgentSphere: A Novel Influencer Maximization Algorithm using Agent-Based Modeling in Social Networks

Jyoti Sunil More[1], Vaishali V. Sarbhukan (Bodade)[2], Yogesh Jadhav[3]

[1]*Department of Computer Engineering, Agnel Charities', Fr. C. Rodrigues Institute of Technology, Vashi, Maharashtra, India.*
[2]*Department of Information Technology, Agnel Charities', Fr. C. Rodrigues Institute of Technology, Vashi, Maharashtra, India.*
[3]*Department of uGDX, Atlas Skilltech University, Mumbai, Maharashtra, India.*

[1]*Corresponding Author : jyotis8582@gmail.com*

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Abstract *- Finding and using influencers to gain benefits is essential for marketing campaigns and information distribution in the field of social network analysis. In order to model and comprehend the intricate dynamics of social networks, this study presents AgentSphere, an inventive Influencer Maximisation Algorithm that makes use of Agent-Based Modeling (ABM). Each agent in the model represents a real-world user, capturing their various traits, actions, and capacities for impact. AgentSphere provides a realistic and nuanced depiction of social relationships through dynamic interactions and information dispersion, which helps with influencer optimisation and correct identification. The creation, application, and assessment of AgentSphere are presented in this research study, demonstrating its efficacy above conventional methods. The outcomes show how flexible AgentSphere is to the ever-changing social network landscape, making it an invaluable resource for influencer maximization in various domains.*

Keywords *- Agent based modeling, Social networks, Social media, Influencer maximization.*

1. Introduction

The dynamic nature of social networks has made it imperative to identify and leverage influencers for marketing, community involvement, and efficient information distribution. Conventional methods for identifying influencers frequently fail to capture the complex dynamics present in real-life social interactions. In addition to enhancing scalability, empirical validation, and multidisciplinary methods, research gaps in influencer maximization utilizing agent-based modeling include modeling agent heterogeneity, dynamic networks, and complicated influence mechanisms. In order to mimic and comprehend the intricate dynamics of social networks, this research presents AgentSphere, a ground-breaking Influencer Maximization Algorithm that leverages the capabilities of Agent-Based Modeling (ABM). Accurate and adaptive modeling of social impact is hampered by the variety of user behaviors and dynamic interactions that characterize it. AgentSphere uses individual agents to mimic the traits, actions, and influence potentials of actual users in order to overcome this difficulty. AgentSphere offers a realistic and nuanced representation of social connections through dynamic interactions and information dissemination, making it possible to identify and optimize influencers precisely. This study explores the design, implementation, and assessment of AgentSphere, demonstrating its efficiency above classical techniques. AgentSphere intends to revolutionize the field of social network analysis by bringing a novel viewpoint on influencer management and providing an adaptable and flexible solution for a range of areas. In the subject of social network analysis, studies on the intricate dynamics of influencers and how they impact the dissemination of information in online communities are becoming more and more common. The dynamic and constantly changing nature of social networks was occasionally ignored by conventional methods in favour of too simplistic metrics like centrality estimations.

2. Related Work

Gomez-Rodriguez et al. (2012) significantly advanced the understanding of influence maximization in continuous-time diffusion networks by analyzing graph-based models. Concurrently, content analysis emerged as an additional topic of study, as demonstrated by the work of [2] Yoganarasimhan Hema (2011) regarding the influence of social structure on the dissemination of knowledge. This approach showed how

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crucial user engagement and viral content are for determining who is influential. However, a shift towards more sophisticated tactics was brought about by the drawbacks of static and heuristic techniques.

Research such as Li Z. et al. (2013) contributed to the popularization of content analysis, particularly when applied to user-generated content. In the context of content-driven impact, [4] Haralabopoulos et al. (2017) investigate the information cascade dynamics. Bakshy et al. (2012) research the mechanics of information dispersion across online social networks. The understanding of the spread of information and the crucial role that influencers play is improved by this study's focus on the relationship between content and network structure. Further instances of machine learning methods applied to influencer identification may be found in the study carried out by [6] Ren, Fuji, and Ye Wu (2013) studied influence that is driven by content. The study by Weng et al. (2014) on the role of information dissemination in the establishment of social networks shows how the focus of the field has turned to temporal dynamics. It was necessary to comprehend how influencers change over time in order to create effective algorithms.

Ghosh et al. (2011) conducted additional research on temporal dynamics and the dynamic nature of social influence. The focus on temporal dynamics is still present thanks to the efforts of Lerman et al. (2016). User behaviour modeling sheds more light on the complex nature of influence in social networks, as demonstrated by Cha et al.'s (2010) study on user influence measurement on Twitter. Bakshy et al.'s (2011) work has contributed to the flourishing field of user behavior modeling studies. Danescu-Niculescu-Mizil et al. (2013) addressed the possible effects of influencer detection on user privacy, which brought ethical issues to light. Narayanan et al. (2018) discuss ethical considerations in influencer detection. Zhou et al. (2015) highlight the junction of influencer detection and cross-platform analysis.

Link prediction in dynamic networks is necessary, according to Ibrahim et al. (2015). They presented a methodology for efficient link prediction. Acquisti et al. (2006) have investigated this need by assessing the efficacy of privacy indicators on several social media platforms. Numerous research projects have been sparked by the need to comprehend social network influencers, and these have all helped to shape the changing field of influencer detection. The work of Leskovec et al. (2007) provides an example of how graph-based models can be used to identify influential nodes and optimize the transmission of information.

The work of Yang et al. (2021) is an excellent example of cross-platform studies, which are crucial for comprehending influencers across various online ecosystems. As influencer detection in social networks is investigated more thoroughly, new findings have added to our knowledge of the many components that make up this intricate phenomenon. Important foundations were established in the field of influence maximization by Kempe et al.'s 2003 work.

Acar et al.'s (2014) paper highlights the possible hazards to user privacy connected with online interactions in the context of ethical considerations. This study highlights the significance of strong privacy protections, as influencer detection algorithms depend more and more on user data. Studies across several platforms continue to be important, as does the work of Hsieh et al. (2017). Kitsak et al. (2010) made a substantial contribution to the area by concentrating on the function of influential spreaders in network dynamics. Machine learning is still essential for influencer identification, according to Sancheng et al.'s (2018) study. Leskovec and Horvitz's (2008) groundbreaking study explores the vast networks that users of instant messaging platforms create on a planetary scale. The foundation for comprehending the extent and difficulties of recognizing prominent users in large and intricate social systems is laid by this research. A powerful paradigm for comprehending and modeling complex dynamics in social networks is agent-based modeling, or ABM. ABM is especially well-suited for capturing the varied and frequently nonlinear interactions among individual agents because of its flexibility and adaptability. Numerous studies have added to the expanding corpus of research on ABM in social network contexts, including insightful information on the dynamics of group behaviors, the spread of information, and the identification of influencers. Its use in modeling is demonstrated by Gonzalez et al. (2011) and Neumann et al. (2009).

The study demonstrates how social impact and network structure shape group behavior and emphasizes the applicability of ABM to the study of real-world events. A thorough summary of the use of ABM in sociology is given by Bianchi et al. (2015) and Flache et al. (2022). ABM is used by Zhanli et al. (2016) and Centola, D. (2010) to study how behaviour spreads in an online social network experiment and the complexities related to it. In order to enhance further the understanding of social contagion, the research offers empirical evidence supporting the function of network structure in the spread of innovations and behaviours. The influence of restricted resources is examined using ABM by Gilbert, N., and Troitzsch, K. G. (2005), Miritello, G., Lara, R., Cebrian, M., and Moro, E. (2013). Researchers are constantly investigating new applications and improving techniques in the dynamic and ever-evolving field of agent-based modeling. These seminal and illustrative studies stimulate future developments in the subject and add to a wider knowledge of ABM in social networks.

2.1. Limitations of Current Approaches in Influencer Maximization

Since influence in social networks is dynamic, current approaches to influencer maximising may miss this fact by depending too heavily on static metrics like centrality measures. These techniques might not treat influencers equally and have trouble capturing changes that rely on the situation. Furthermore, they frequently place more emphasis on structural positions than on user behaviours or content-related aspects. Network scalability problems might occur as they get bigger.

3. Potential of Agent-Based Modeling (ABM) in Influencer Maximization:

A viable substitute is provided by Agent-Based Modeling (ABM), which views people as independent agents with distinct characteristics and actions. Contextual sensitivity is made possible by ABM, which also adapts to different domains and captures the dynamic interactions between agents across time. Beyond structural measurements, it excels at modeling the complex and context-dependent character of influence. Because of its versatility, capacity to model a wide range of user behaviors, and attention to emerging characteristics, ABM is a highly effective method for comprehending and improving influencer identification in social networks. The shortcomings of the influencer maximization techniques used today are addressed by ABM, which offers a more thorough and practical solution. The goal of AgentSphere is to fill in the gaps in the literature on Agent-Based Modeling (ABM) for social network influencer maximisation. The objective of AgentSphere is to create models that can adjust over time to changes in user behaviours and network topologies, as dynamic influencer identification techniques are frequently absent from ABM investigations. AgentSphere also aims to contribute to contextual sensitivity by taking into account temporal variations in user interests and topic relevancy. The model incorporates more sophisticated behavioural models that represent the variety of ways individuals exert influence in an effort to address the simplicity of user behaviours in the ABM literature that currently exists. Additionally, AgentSphere strives for cross-domain flexibility, acknowledging that influencers could differ dramatically between various thematic or cultural contexts.

The lack of standardized evaluation metrics for influencer maximization in ABM is another gap, and AgentSphere intends to propose robust metrics considering both quantitative and qualitative aspects of influence. Realistic simulation of content diffusion is an additional focus, with AgentSphere aiming to improve the realism of content diffusion simulations by considering factors such as content virality and user engagement. Ethical considerations, often overlooked in existing literature, are also integrated into AgentSphere, addressing concerns like user privacy and the potential consequences of influencer identification. The model further targets the exploration of user engagement metrics, seeking a comprehensive understanding of their influence on influencer identification. By addressing these gaps, AgentSphere aims to contribute to the refinement and advancement of ABM approaches for influencer maximization, providing a more accurate and adaptable model for understanding and optimizing influence dynamics in social networks.

A novel influencer maximisation technique for social networks, AgentSphere is built on Agent-Based Modeling (ABM) and simulates the dynamic interactions of autonomous agents that represent persons in the network.

Taking into account the complex nature of influence in changing social environments, the algorithm seeks to identify influential nodes across time. An extensive description of the AgentSphere algorithm may be found here.

3.1. Agent Representation

Each individual in the social network is modeled as an autonomous agent with specific attributes, behaviours, and influence capacities. Attributes may include demographic information, historical interactions, and topical interests, allowing for a nuanced representation. The network can be initialized in three steps, as shown below.

Initialize:
Define social network structure
Assign attributes and behaviors to agents
Set initial conditions for the simulation

Algorithm: SN_InfluenceMaximization for AgentSphere

The following features of the network are needed to be initialized for the network to keep track of the simulation of this agent-based modeling approach:

n_agents: It represents the total number of agents defined in the social network

n_connections: It represents total number of connections defined in the initial network

n_steps: It defines the total number of simulation steps in the procedure

The overall working of the proposed algorithm Agentsphere is depicted in Figure 1. The functions are defined in detail as follows:

Function: InitializeNetwork(n_agents, n_connections)

- With n_agents nodes and an edge probability of n_connections/n_agents, construct an Erdos-Renyi graph (G)
- Return G

Function: InitializeAgents(G)

For each node in G:

- Set the 'influence' attribute to a random float between 0 and 1
- Add other attributes and behaviors as needed
- Return G

Function: UpdateNetwork(G)

- Implement dynamic network evolution based on agent interactions.
- This might involve changing the number of edges according to how the agents behave.
- Return the updated network G.

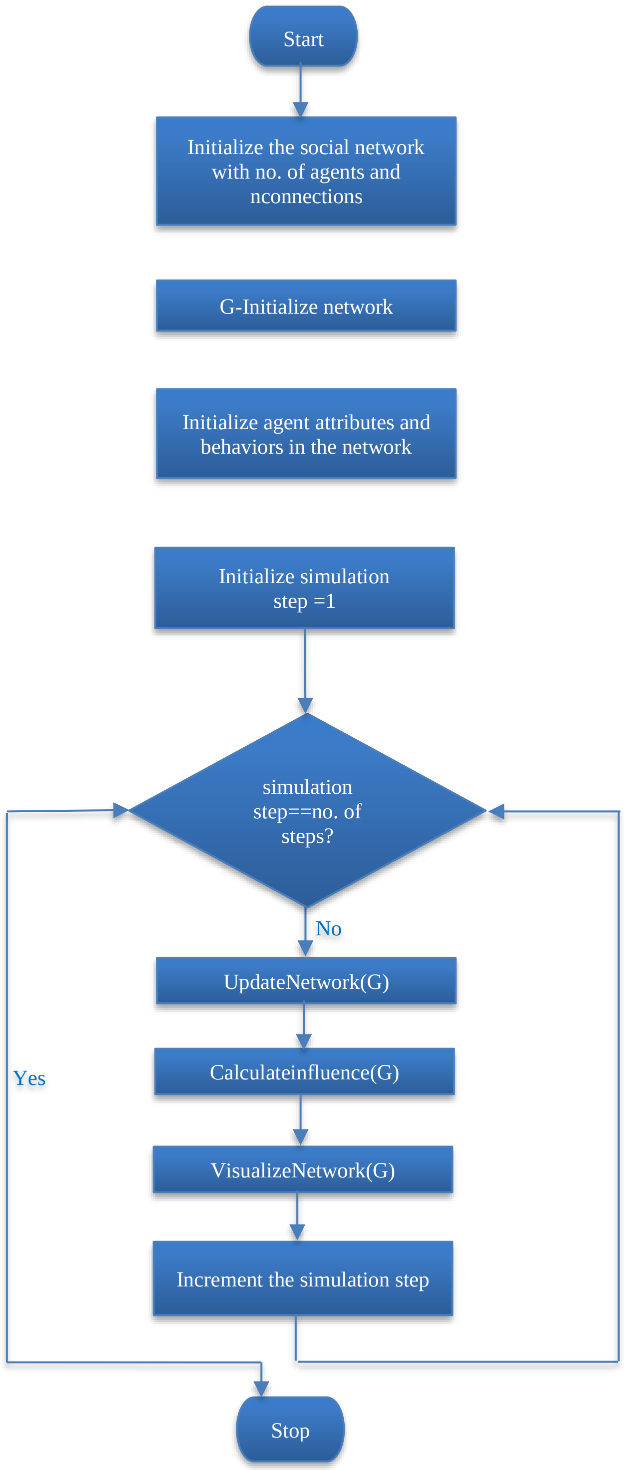

Fig. 1 Flowchart for the proposed algorithm: AgentSphere

Function: CalculateInfluence(G)

- Apply the influence calculation using behaviours and structural indicators.
- This could entail taking user interaction, content distribution, etc. into account.
- Return the updated network G.

Function_VisualizeNetwork(G)

- Use a spring layout for network visualization.
- Scale node sizes based on the 'influence' attribute.
- Display the network plot using matplotlib.
- End of visualization.

4. Results and Discussion

For visualization, the parameters are set as follows: Set n_agents = 20, n_connections = 30, n_steps = 5. Call SNInfluenceMaximization (n_agents, n_connections, n_steps)

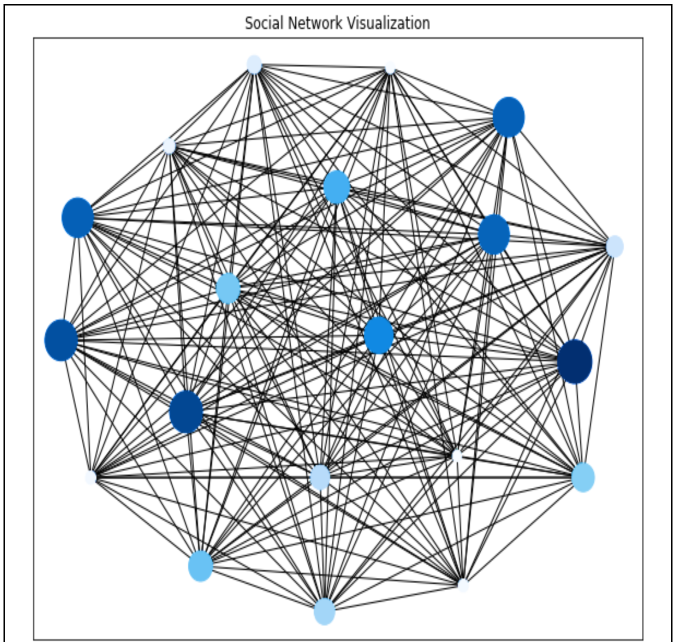

Fig. 2a Simulation step(n_step) =1

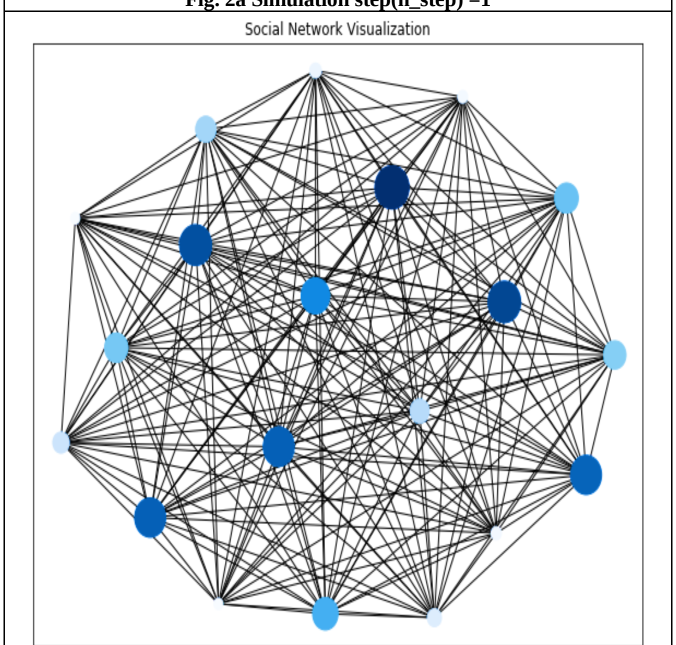

Fig. 2b Simulation step(n_step) =2

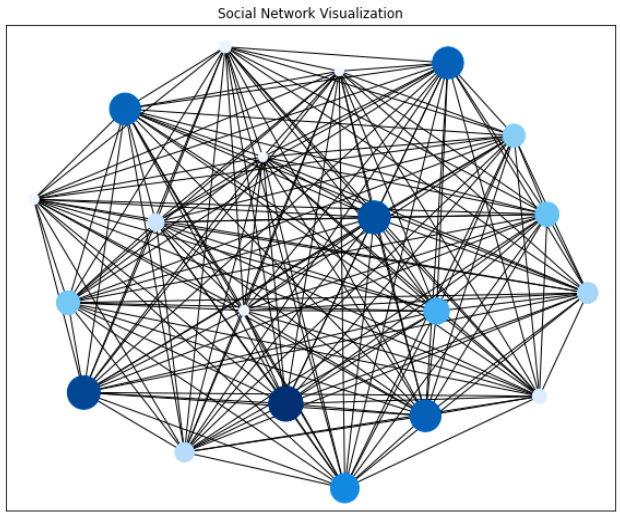

Fig. 2c Simulation step(n_step) =3

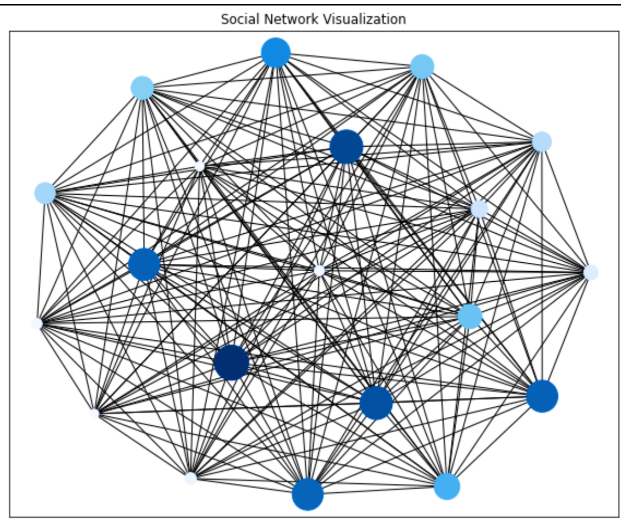

Fig. 2d Simulation step(n_step) =4

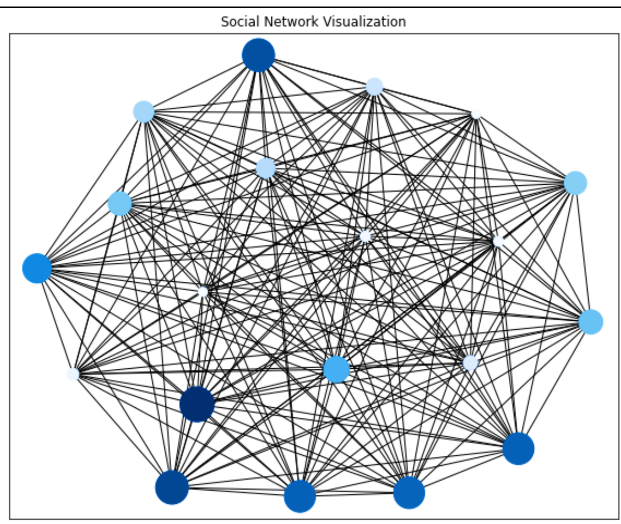

Fig. 2e Simulation step(n_step) =5

Fig. 2 Visualization of simulation of the proposed algorithm: AgentSphere

Figure 2 shows the visualization of the simulation of the proposed algorithm. Figures 2a to 2e show the individual agent behaviour, at each step. It is important to note that the node sizes are proportional to the influence values. It can be clearly noted that eventually, step-wise, the influence is maximized. Agent-based modeling (ABM) for influencer maximization in social networks is guided by design principles that prioritize individual-based representation, dynamic interactions, and contextual sensitivity. ABM captures the diverse behaviors of agents, allowing for a nuanced understanding of influence dynamics. The model adapts to different domains and considers contextual factors like topic relevance and cultural nuances. Individual-level influence metrics account for both structural attributes and behavioral patterns. ABM simulates realistic content diffusion, incorporating factors such as virality and user engagement. The framework is designed to be adaptable, ensuring its applicability to a wide range of social contexts. Additionally, ethical considerations, such as user privacy and responsible influence use, are integrated into the modeling process. Overall, ABM provides a flexible and dynamic approach that goes beyond traditional metrics, offering a more accurate representation of the complexities in social interactions and information spread within networks.

4.1. Challenges

While influencer detection algorithms offer a more nuanced approach compared to traditional methods, they are not without their limitations. Some key challenges include:

4.1.1. Data Limitations

Algorithms are often limited by the data available to them, which may not capture the full scope of a user's influence. Dynamic nature of influence: Influence is a fluid concept that can fluctuate over time. Algorithms may struggle to keep pace with these dynamic changes.

4.1.2. Gaming the System

Certain individuals may engage in artificial practices like buying followers or employing bots to inflate their perceived influence, posing a challenge for algorithms.

4.2. Comprehensive Evaluation of AgentSphere's Performance

An extensive analysis of AgentSphere's effectiveness employs a multipronged method to appraise its influencer-maximising potential in a social network. The efficacy of the algorithm may be determined by looking at metrics like the number of influencers that have been identified and the way that influence has spread over time. By comparing it with baseline approaches, one may assess its accuracy and potential for improvement. Analysing network properties like density and connectedness can help us comprehend how flexible the network is with different kinds of structures. Evaluations of the algorithm's resilience and dynamic adaptation measure how well it responds to changes in time and how well it can tolerate disturbances. For bigger networks, scalability analysis takes memory utilization and computational efficiency into account. Convergence rate analysis gauges the stability of the algorithm throughout simulation steps, whereas sensitivity analysis on algorithm parameters investigates their effect on performance. By showing influence dynamics and network structures, visualization facilitates interpretation. The dependability of the evaluation is further strengthened by statistical significance testing and real-world validation, and ethical considerations help to assure fairness and reduce biases in the influencer selection process. This thorough assessment methodology offers a sophisticated perspective of AgentSphere's advantages and disadvantages in many situations.

5. Conclusion

Influencer detection algorithms play a crucial role in navigating the complex landscape of social media. By understanding the methodologies, strengths, and limitations of these algorithms, valuable insights can be gained into how influence is measured and manifested online. As social media continues to evolve, ongoing research and development are crucial to refine existing algorithms and adapt to the ever-changing dynamics of the online world. Ultimately, this deeper understanding can empower individuals to make informed decisions about the information they consume and the influence they encounter online.

Future Research

A fundamental understanding of influencer detection algorithms is presented in this research study. Subsequent investigations may examine the moral ramifications of using algorithms to pinpoint influential users. The creation of increasingly sophisticated and resilient algorithms that are able to represent influence's complex nature. Social media platforms' effects on influence dynamics and the development of techniques for identifying influencers. More insights could be gained into a thorough grasp of the intricate link between algorithms, influencers, and power dynamics within the changing social media ecosystem by carrying out more research in these areas.

References

[1] Manuel Gomez Rodriguez, and Bernhard Schölkopf, "Influence Maximization in Continuous Time Diffusion Networks," *Proceedings of the 29th International Conference on Machine Learning (ICML)*, pp. 1661-1669, 2012. [CrossRef] [Publisher Link]

[2] Hema Yoganarasimhan, "Impact of Social Network Structure on Content Propagation: A Study Using Youtube Data," *Quantitative Marketing and Economics*, vol. 10, pp. 111-150, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[3] Zongchao Li, and Cong Li, "Tweet or "Re-Tweet"? An Experiment of Message Strategy and Interactivity on Twitter," *Internet Research*, vol. 24, no. 5, pp. 648-667, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[4] Giannis Haralabopoulos, Ioannis Anagnostopoulos, and Sherali Zeadally, "Viral Content Propagation in Online Social Networks," *arXiv*, pp. 1-12, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[5] Eytan Bakshy et al., "The Role of Social Networks in Information Diffusion," *Proceedings of the 21st International Conference on World Wide Web*, pp. 519-528, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[6] Fuji Ren, and Ye Wu, "Predicting User-Topic Opinions in Twitter with Social and Topical Context," *IEEE Transactions on Affective Computing*, vol. 4, no. 4, pp. 412-424, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[7] Xiaoyan Qiu et al., "Limited Individual Attention and Online Virality of Low-Quality Information," *Nature Human Behaviour*, vol. 1, no. 7, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[8] Lilian Weng et al., "The Role of Information Diffusion in the Evolution of Social Networks," *Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 356-364, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[9] Rumi Ghosh et al., "Time-Aware Ranking in Dynamic Citation Networks," *2011 IEEE 11th International Conference on Data Mining Workshops*, Vancouver, BC, Canada, pp. 373-380, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[10] Kristina Lerman, and Rumi Ghosh, "Information Contagion: An Empirical Study of the Spread of News on Digg and Twitter," *Proceedings of the Eighth International Conference on Social Computing (ICSC)*, vol. 4, no. 1, pp. 90-97, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[11] Meeyoung Cha et al., "Measuring User Influence in Twitter: The Million Follower Fallacy," *Proceedings of the 4th International AAAI Conference on Weblogs and Social Media*, vol. 4, pp. 10-17, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[12] Eytan Bakshy et al., "Everyone's an Influencer: Quantifying Influence on Twitter," *Proceedings of the Fourth ACM International Conference on Web Search and Data Mining*, pp. 65-74, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[13] Cristian Danescu-Niculescu-Mizil et al., "No Country for Old Members: User Lifecycle and Linguistic Change in Online Communities," *Proceedings of the 22nd ACM International Conference on World Wide Web*, pp. 307-318, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[14] Robyn Caplan et al., "Algorithmic Accountability: A Primer," *Data & Society*, pp. 1-28, 2018. [Google Scholar] [Publisher Link]

[15] Nahla Mohamed Ahmed Ibrahim, and Ling Chen, "Link Prediction in Dynamic Social Networks by Integrating Different Types of Information," *Applied Intelligence*, vol. 42, pp. 738-750, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[16] Alessandro Acquisti, and Ralph Gross, "Imagined Communities: Awareness, Information Sharing, and Privacy on the Facebook," *Privacy Enhancing Technologies, Lecture Notes in Computer Science*, vol. 4258, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[17] Jure Leskovec et al., "Cost-Effective Outbreak Detection in Networks," *Proceedings of the 13th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 420-429, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[18] Yi Yang et al., "Cross-Platform Comparison of Framed Topics in Twitter and Weibo: Machine Learning Approaches to Social Media Text Mining," *Social Network Analysis and Mining*, vol. 11, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[19] David Matthias Kempe, Jon Michael Kleinberg, and É Tardos, "Maximizing the Spread of Influence Through a Social Network," *Proceedings of the Ninth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 137-146, 2003. [CrossRef] [Google Scholar] [Publisher Link]

[20] Arvind Narayanan, and Vitaly Shmatikov, "De-Anonymizing Social Networks," *2009 30th IEEE Symposium on Security and Privacy*, Oakland, CA, USA, pp. 173-187, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[21] Haiqian Gu et al., "Cross-Platform Modeling of Users' Behavior on Social Media," *2018 IEEE International Conference on Data Mining Workshops (ICDMW)*, Singapore, pp. 183-190, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[22] Maskim Kitsak et al., "Identification of Influential Spreaders in Complex Networks," *Nature Physics*, vol. 6, pp. 888-893, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[23] Sancheng Peng et al., "Influence Analysis in Social Networks: A Survey," *Journal of Network and Computer Applications*, vol. 106, pp. 17-32, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[24] Jure Leskovec, and Eric J. Horvitz, "Planetary-Scale Views on a Large Instant-Messaging Network," *Proceedings of the 17th ACM International Conference on World Wide Web*, pp. 915-924, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[25] Martin Neumann, "Emergence as an Explanatory Principle in Artificial Societies. Reflection on the Bottom-Up Approach to Social Theory," *Epistemological Aspects of Computer Simulation in the Social Sciences, Lecture Notes in Computer Science*, vol. 5466, pp. 69-88, 2009. [Google Scholar] [Publisher Link]

[26] Sandra González-Bailón et al., "The Dynamics of Protest Recruitment through an Online Network," *Scientific Reports*, vol. 1, pp. 1-17, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[27] Andreas Flache, Michael Mäs, and Marijn A. Keijzer, *Chapter4: Computational Approaches in Rigorous Sociology: Agent-based Computational Modeling and Computational Social Science*, Handbook of Sociological Science, Edward Elgar Publishing, pp. 57-72, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[28] Federico Bianchi, and Flaminio Squazzoni, "Agent-Based Models in Sociology," *Wiley Interdisciplinary Reviews: Computational Statistics*, vol. 7, no. 4, pp. 284-306, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[29] Zhanli Sun et al., "Simple or Complicated Agent-Based Models? A Complicated Issue," *Environmental Modelling & Software*, vol. 86, pp. 56-67, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[30] Damon Centola, "The Spread of Behavior in an Online Social Network Experiment," *Science*, vol. 329, no. 5996, pp. 1194-1197, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[31] Nigel Gilbert, and Klaus G. Troitzsch, *Simulation for the Social Scientist*, 2nd ed., McGraw-Hill Education, pp. 1-295, 2005. [Google Scholar] [Publisher Link]

[32] Giovanna Miritello et al., "Limited Communication Capacity Unveils Strategies for Human Interaction," *Scientific Reports*, vol. 3, pp. 1-7, 2013. [CrossRef] [Google Scholar] [Publisher Link]