Using AI: Hints from Agent-based Model of Fake News Diffusion

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Abstract

In this study, Agent-based modeling is introduced as a methodology to reveal the dynamical diffusion process of fake news along with the correction process going synchronically theoretically. This finding can be used for the usage of Large Language Models (LLMs) to decrease the spread of disinformation. The model can examine the efficacy of three potential solutions to decrease the spread of misinformation: Individual punishments for rumor diffusion are not useful; The number of rationales influences the scale of rumors spread and ratio of truth-rumor dramatically; The biggest impact is made by the portion of people who claim the truth to the public, which impressively shows a reverse ratio of truth-rumor. The effectiveness in correction in individual aspect give the help from LLMs in detecting and correcting so important. The study then discussed the updated development of LLMs used in misinformation and possible prospect according to the diffusion theory.

Keywords: ABM, LLMs, fake news, diffusion

Using AI: Hints from Agent-based Model of Fake News Diffusion

We encounter scandals in our daily lives. When surfing the internet, we see false news in astonishingly appealing headings to induce our views. The bad impact of fake news can be particularly sensed when coming to politics. Cases of misinformation during the 2016 presidential election and unreal hate speech of enemy countries like China fully tell us that this false information can trigger negative emotions and even social unrest. How to deal with the diffusion of them on a broad scale? What is the effective solution to them?

Literature Review

False information flooding our daily lives is particularly notable with the rise of globalization and the development of social media (Wittenberg & Berinsky, 2020). The harm and pattern of the diffusion of fake news have attracted the attention of researchers from numerous disciplines, namely communications, political science, psychology, economics, business, and computer science (Edson, 2019). The main concerns of fake news are the definition and scope of the problem, potential causes, and possible solutions to the issue, within which the spread of fake news is a hot topic.

The spread of misinformation is analyzed in numerals ways under different social conditions. Sights are provided by various quantitative empirical study analyzed the spread of true and false news online, finding that falsehood diffused significantly further, faster, deeper, and more broadly than the truth in all categories of information (Vosoughi et al., 2018; Lazer et al., 2018). Another example by Shin et al. (2017) explored the lifecycle of political rumors on Twitter, observing that fake news tends to be rebroadcasted more frequently, keeping it alive in the public eye for longer periods. Some research believes it is because fake news is more novel than true news, that people are more likely to share novel information (Vosoughi et al., 2018). There is a tradition of delving into psychological perspective to reveal the reasons for people’s believing in false information in cognitive aspects, which could be traced back to *The Case for Motivated Reasoning* released in 1990. Kunda reveals that the motivation to generate certain conclusions is influenced by a biased set of cognitive processes. Thus, people are more likely to do reasonings that they want to arrive at, but their ability to do so is constrained by their ability to construct seemingly reasonable justifications for these conclusions. After analyzing the case of the political fake news in the 2016 presidential election, the result is given that cognitive repetition influences people's subsequent perceptions of the accuracy of false information than political ideology (Pennycook, 2018). Similarly, Pennycook and Rand (2019) suggest that susceptibility to fake news is driven more by lazy thinking than by partisan bias per se using the Cognitive Reflection Test.

Instead of individual conception, some research focuses on modeling the structure of the diffusion process, bringing new insight into the field of misinformation studies. Some research introduced a data-driven percolation model mimicking rumor-spreading network structures on social media and found that homogeneity appears to be the primary driver for the diffusion of contents (Del Vicario et al., 2016). In another attempt, scientists used a time-serious model for the dynamics of fake news on Twitter, revealing the fluctuations of rumors over time (Kwon et al.2022).

While individual surveys provide insights into personal reactions to fake news, they often fail to capture the complex social interactions and dynamics that influence the spread of misinformation. The emergence happens when the diffusion process is no longer an individual-level decision but an integral interaction among the crowd. With the rise in computational social science, scientists try to use complex models like Agent-Based Models (ABM) to understand the spread of fake news. Research in 2022 applied a point process model to understand the online dissemination of fake news using data collected on Twitter. The proposed model describes the spread of a fake news item as a two-stage process: initially, fake news spreads as a piece of ordinary news; then, when most users start recognizing the falsity of the news item, that itself spreads as another news story. However, their model primarily captures the initial spread and recognition phases, without delving into the truth that rumors can be corrected dynamically.

In a study newly released on March 2024, scientists modeled the diffusion of misinformation as a coordination game. They introduced their model to synthetic square lattices and small-world networks to find out that sanctioners can help contain fake news when placed strategically. The appliance of ABM offered a comprehensive understanding that surveys and simple statistic models alone cannot provide. However, this model treats the spread of fake news and truth separately without noticing the integral relationship between false information and corrected facts. This is my starting point of this research, to focus on the correction dynamic within the diffusion of rumor spreading process.

Methodology

I use NetLogo 6.3.0 as the platform to build my Agent-based model. I got inspired by the Termites Model and decided to simplify turtles to patches with enforcement to better run the model. As for diffusion structure, I have considered adding links to the primary model built with turtles but find it’s not concentrating on the main topic I am concerned. Instead, I use the wide-bridge theory to depict the difference in the diffusion of rumors and facts. Rumors can be spread if any of the 8 neighbors around the “crowd” agent is contacted by rumor. The correction process can, however, only be spread if more than or equal to 3 out of eight neighbors are corrected. There are two advantages to this adjustment: 1. Though people seem to be connected by the internet, the flourishment of all kinds of information again with biased recommendation algorithms, people tend to form clustered subgroups each sharing information of different aspects. The spatial connection of the agents in the model can be seen as the clustered form of the masses. 2. The simplified model reacts faster to my instructions to multiple changes in variables. My computer shut down several times when running the previous model with complex linear links between turtles.

Model Building

The ABM is built using patches as individuals, each owning 150 degrees of “life”. A default 33X33 (1089) patches are generated when set up. “Life” is the willingness of agents to interact with others. Two kinds of information can be spread among the masses: “Scandals” and “Truth”, colored in green and red. Scandals represent fake news in the context and could be set up in any numbers smaller than 1089 as a global variable. Two statuses cannot be spread namely “Neutral” (grey) and “Muted” (black). “Neutral” agents are those who are not spreading information to other agents. “Muted” are those who have “life” smaller than or equal to 0, meaning no interaction with agents around.

People's reactions to fake news vary significantly, influencing the dynamics of information spread across social platforms. A study on the 2016 presidential election exposed that only 1% of individuals accounted for 80% of fake news source exposures, and 0.1% accounted for nearly 80% of fake news sources shared (Grinberg et al., 2019). Research on social media users in Singapore found that 73% of the respondents chose to ignore posts containing fake news on social media, while only 27% would report and correct the false news posts they came across on social media. They would only offer corrections when the issue is strongly relevant to them and to people with whom they share a strong and close interpersonal relationship. (Edson et al., 2019). Therefore, in the model, I assumed that there are three types of agents in the model, namely “wise”, “rationale”, or “crowd”. The proportion of the three kinds of agents could be adjusted. Here are the enforcements:

1. “Crowd”: Nearby agents easily influence the “crowd” agents, which are also contagious. They are volatile. They adopt truth and turn “green” if the number of agents nearby that are green is greater than or equal to 3. They adopt truth and turn “red” if the number of agents nearby that are red is greater than or equal to 1. They keep switching color and influence agents around them until their life is smaller than or equal to 0.

2. “Rationale”: These are rational people who can sense false news easily and choose not to spread it. They are indifferent to truth as well. They keep neutral (grey) until their life is smaller than or equal to 0.
3. “Wise”: These represent people who can sense false news easily the same time trying to correct them and spread the facts to the public. They become green when exposed to fake news and remain green to influence agents around them until their life is smaller than or equal to 0.

Empirical research has demonstrated that false news travels more extensively, quickly, deeply, and widely than true information across all types of content (Vosoughi et al., 2018; Lazer et al., 2018). They are also more frequently re-shared, thus maintaining their presence and relevance over extended periods (Shin et al., 2017). So, I have also imposed two global variables, namely “Truth-cost” and “Scandal-cost” to adjust the cost of spreading truth and the cost of spreading scandals. “Truth-cost” scale from 0-50, “Scandal-cost” scale from 0-20. It is the default that the cost of the latter is lower than the former.

The diffusion of too much information causes severe impacts individually and socially. A study on E-commerce platforms reveals that perceived information overload has a positive influence on online return intention through impulsive buying behavior, and perceived information overload has a positive influence on online return intention through cognitive dissonance (Lv & Liu,2022). Misinformation may trigger societal risks due to its potential to influence elections, incite fear, and cause social unrest (Lazer et al., 2018). Some researchers have shown that only a small fraction of the online audience is exposed to fake news, for this small group of individuals, the impact of fake news can be quite substantial (Tandoc, 2019; Grinberg et al., 2019; Nelson & Taneja, 2018). Though there isn’t a good summary of the potential negative impact of both fake news and information overload, I set up the limit of “life” for all agents initially set as 150. If the “life” of a certain agent is smaller than or equal to 0, it can no longer react to any other information and turn “black”. It could be understood as either too tired and indifferent to the surrounding world or very bad and irreversible impact.

Results

For the model, I want to try to set up the initial type that is most similar to the real world as the control group to start the experiment. A study on the 2016 presidential election exposed that only 1% of individuals accounted for 80% of fake news source exposures, and 0.1% accounted for nearly 80% of fake news sources shared (Grinberg et al., 2019). Research on social media users in Singapore found that 73% of the respondents chose to ignore posts containing fake news on social media, while only 27% would report and correct the false news posts they came across on social media (Edson et al., 2019). So I set up the origin model of Truth-cost = 20, Scandal-cost = 5, scandals = 10, probability-of-wises = 0.10, probability-of-rationales = 0.70. The outcome can be seen in *Figure 4 Real-world Model*. Only a small amount of people are exposed to fake news that brings bad outcomes. At the same time, only a very small amount of people would correct the misinformation. Still, fake news grows more quickly than truth but is much smaller in amount and becomes steady around 124.

1. Will punishments help?

Hypothesis 1*: The diffusion of fake news can be limited by the cost of spreading. The number of scandals spread decreases significantly after imposing punishment.*

To imply punishment, I imposed a higher scandal cost of 20 to be the same as the truth cost, to see the change in the number of rumors and facts that remained. The tick will automatically stop in 30 ticks if the diffusion process no longer exists, and the color of patches becomes steady. If the patches keep altering colors, the tick goes on until the phenomena stop.

The result is that the graph of the number of truths and rumors over time remains almost the same when a punishment is imposed, hypothesis 1 is false. The number of fake news remains steady at 131, and the ratio of scandals/truth has no statistically significant change compared to the *real-world model*. The result can be seen in *Figure 5* in the Appendix. As a result, individual punishment cannot limit the spread of disinformation vividly. This can be proved by cases that though celebrities give out several lawyer letters to stop rumors, barely any decrease in scandals can be observed.

2. Will rationality help?

Hypothesis 2*: The portion of rationales influences the number of scandals spread and the truth-rumor ratio. With a higher proportion of people who don't spread rumors, the number of false information diffused declines, and the truth-rumor ratio increases.*

Model outcome can be seen in *Figure 6*, which is set with Truth-cost = 20, Scandal-cost = 5, scandals = 10, probability-of-wises = 0.10, probability-of-rationales = 0.80. The number of rumors and truth fluctuate at the beginning and then becomes steady for scandals of 24 and truths of 13, which is much smaller than the real-world model. The truth-rumor ratio is also higher to be 0.54 compared to 0.31. However, the absolute amount of the truth is dramatically decreased, and so do the general scale of the impact. As a result, more indifferent people can stop spreading rumors but also cut down the impact of the incident, which is bad for diffusion.

3. Will corrections help?

Hypothesis 3*: The spread of rumors is influenced by the portion of people who intend to correct the misinformation. As the probability of the wises rises, the number of rumors decreases and the number of truths rises.*

I set up the two models to better reveal the trend. The first model *Figure 7* is set with Truth-cost = 20, Scandal-cost = 5, scandals = 10, probability-of-wises = 0.20, probability-of-rationales = 0.70. The second model *Figure 8* is set with Truth-cost = 20, Scandal-cost = 5, scandals = 10, probability-of-wises = 0.20, probability-of-rationales = 0.60. At the start, both rumors and truths increase sharply but soon stabilize, with scandals at 89 and truths at 87, where they remain steady. Initially, false information peaks higher than truths but is quickly overtaken, eventually balancing out and stabilizing at similar levels. This pattern repeats at a larger scale, with scandals reaching 145 and truths 150, following a similar trajectory of initial surge, overtaken by truths, and eventual stabilization. This behavior mirrors what is depicted in Figure 7 but on a larger scale.

The outcomes of some ideal types can be seen in the *appendix*. Table 1 calculated the impact of the change in rationales and the wises. In conclusion, Increasing the proportion of rational and wise individuals in the population generally results in a higher dissemination of truths compared to scandals. At the extremes (1.00 probability of rationales, 0.00 of wises), scandals dominate completely with no truth spread at all. As the probability of the wise increases, even slightly, the number of truths begins to increase significantly. For instance, moving from 0% wise to 10% wise results in a noticeable increase in truths spread. Scenarios where the combined probability of rational and wise agents is higher not only have more truths spread but also show a healthier truth-to-scandal ratio, crossing over to more truths than scandals when the wise proportion is at least 20%.

Table 1

Scale of diffusion

Probability-of-rationales	Probability-of-wises	Number of Truths	Number of Scandals	Truth-Scandal Ratio	Total Influenced Number
1.00	0.00	0	10	0.00	10
0.80	0.10	13	24	0.54	37
0.70	0.10	38	124	0.31	162
0.60	0.10	81	311	0.26	392
0.70	0.20	89	87	1.02	176
0.60	0.20	150	145	1.03	295

The Help From Large Language Models

The diffusion of fake news causes severe impacts. Misinformation may trigger societal risks due to its potential to influence elections, incite fear, and cause social unrest (Lazer et al., 2018). This study generally reveals that individual rationality is the key to dealing with misinformation. However, possible solutions to this take much time and are pricey, like implanting educational and informational programs that promote rational thinking, increasing the population's ability to critically analyze information can act as a natural deterrent to the spread of fake news. Also, deploying targeted information campaigns in communities or nodes to promote people's willingness to correct the false news they come across is almost a fantasy.

However, with the help of LLMs, this educational and propaganda pressure can be transferred. Several essays have focused on detecting misinformation context using large language models. The detecting process is simple: train the models using news stories, social media posts, videos on YouTube, and other digital content, and the output would be a label indicating real or fake. Once the trainer learns how input predicts output, we could deploy the predictor in the real world where it's only given inputs (that it hasn't seen before), and ask it to predict the outputs. However, the correctness of judging fake news is the answer given by humans who somehow seem to be too proud of their ability to label fake news. Some studies have also used framework to study the basic pattern of misinformation. I think we can also evaluate its diffusion pattern in the future of detecting fake news.

Pathetically, the current study also exposes the spreading of fake information generated by social bots without purpose. Successful low-credibility sources are heavily supported by social bots, suggesting that curbing social bots may be an effective strategy for mitigating the spread of online misinformation. When using GPT for essay writing, we can also find the chat box faking essays on certain topics with somehow incredibly relevant titles, abstracts, and names of not existing authors. One of my good personal solutions to this is to ask the AI to list all the essays it mentioned with direct links.

Though false information has toxic impacts, we can also use its ability to do good. False news has novel and interesting headings to attract people's attention, which could be learned by media content producers to release facts with more attractive headings. An example is that some Politic Official Accounts in China use very wrong but appealing headings to trigger people to click in and view in WeChat. Headings like "Buying an academician title for 400,000 yuan" are corrections of false information spread online that you can pay for the highest academician title in China. Some people imagined the story of the side door when seeing the newly awarded scientist at an astonishing young age. The post uses this heading similar to fake news but clarifies the young researcher's contribution in the context. It is therefore much accessible for training LLMs to learn the pattern of successful news headings and automatically generate appealing headings for real news.

References

Abdulqadir Rahomee Ahmed Aljanabi and Waleed KH Mohamed AL-Hadban. 2023. “The Impact of Information Factors on Green Consumer Behaviour: The Moderating Role of Information Overload.” Information Development. doi: 10.1177/02666669231207590.

Aljanabi, Abdulqadir, Abdulqadir Rahomee Ahmed Aljanabi, and Abdulqadir Rahomee Ahmed Aljanabi. 2021. “The Impact of Economic Policy Uncertainty, News Framing and Information Overload on Panic Buying Behavior in the Time of COVID-19: A Conceptual Exploration.” International Journal of Emerging Markets. doi: 10.1108/ijoem-10-2020-1181.

Anon. n.d.-a. “Can A.I. Stop Fake News?” The University of Chicago Booth School of Business. Retrieved May 8, 2024 (https://www.chicagobooth.edu/review/can-ai-stop-fake-news).

Anon. n.d.-b. “Misinformation and Its Correction (Chapter 8) - Social Media and Democracy.” Retrieved May 9, 2024 (https://www.cambridge.org/core/books/social-media-and-democracy/misinformation-and-its-correction/61FA7FD743784A723BA234533012E810).

Chloe Wittenberg, Wittenberg C, Chloe Wittenberg, Adam J. Berinsky, Adam J. Berinsky, and Adam J. Berinsky. 2020. “Misinformation and Its Correction.” 163–98. doi: 10.1017/9781108890960.009.

Chris J. Vargo, Chris J. Vargo, Лэй Гуо, Lei Guo, Michelle A. Amazeen, and Michelle A. Amazeen. 2018. “The Agenda-Setting Power of Fake News: A Big Data Analysis of the Online Media Landscape from 2014 to 2016.” New Media & Society 20(5):2028–49. doi: 10.1177/1461444817712086.

Del Vicario, Michela, Alessandro Bessi, Fabiana Zollo, Fabio Petroni, Antonio Scala, Guido Caldarelli, H. Eugene Stanley, and Walter Quattrociocchi. 2016. “The Spreading of Misinformation Online.” Proceedings of the National Academy of Sciences of the United States of America 113(3):554–59. doi: 10.1073/pnas.1517441113.

Edson C. Tandoc, Edson C. Tandoc, Zheng Wei Lim, Zheng Wei Lim, Richard Ling, and Richard Ling. 2018. “Defining ‘Fake News’: A Typology of Scholarly Definitions.” Digital Journalism 6(2):137–53. doi: 10.1080/21670811.2017.1360143.

Eytan Bakshy, Eytan Bakshy, Solomon Messing, Solomon Messing, Lada A. Adamic, and Lada A. Adamic. 2015. “Exposure to Ideologically Diverse News and Opinion on Facebook.” Science 348(6239):1130–32. doi: 10.1126/science.aaa1160.

Farhoundinia, Bahareh, Selcen Ozturkcan, and Nihat Kasap. 2023. “Fake News in Business and Management Literature: A Systematic Review of Definitions, Theories, Methods, and Implications.” Aslib Journal of Information Management. doi: 10.1108/AJIM-09-2022-0418.

Gordon Pennycook, Gordon Pennycook, Tyrone D. Cannon, Tyrone D. Cannon, and David G. Rand. 2018. “Prior Exposure Increases Perceived Accuracy of Fake News.” Journal of Experimental Psychology: General 147(12):1865–80. doi: 10.1037/xge0000465.

Hunt Allcott, Hunt Allcott, Matthew Gentzkow, and Matthew Gentzkow. 2017. “Social Media and Fake News in the 2016 Election.” Journal of Economic Perspectives 31(2):211–36. doi: 10.1257/jep.31.2.211.

Jang, S. Mo, and Joon K. Kim. 2018. “Third Person Effects of Fake News: Fake News Regulation and Media Literacy Interventions.” Computers in Human Behavior 80:295–302. doi: 10.1016/j.chb.2017.11.034.

Jones, Matthew I., Scott D. Pauls, and Feng Fu. 2024. “Containing Misinformation: Modeling Spatial Games of Fake News.” PNAS Nexus 3(3):pgae090. doi: 10.1093/pnasnexus/pgae090.

Jun Lv, Jun Lv, Xuan Liu, Xuan Liu, and Xuan Liu. 2022. “The Impact of Information Overload of E-Commerce Platform on Consumer Return Intention: Considering the Moderating Role of Perceived Environmental Effectiveness.” International Journal of Environmental Research and Public Health 19(13):8060–8060. doi: 10.3390/ijerph19138060.

Lazer, David, Matthew Baum, Yochai Benkler, Adam Berinsky, Kelly Greenhill, Filippo Menczer, Miriam Metzger, Brendan Nyhan, Gordon Pennycook, David Rothschild, Michael Schudson, Steven Sloman, C. Sunstein, Emily Thorson, Duncan Watts, and Jonathan Zittrain. 2018. “The Science of Fake News.” Science 359:1094–96. doi: 10.1126/science.aao2998.

Maria Koutamanis, Maria Koutamanis, Helen Vossen, Helen G. M. Vossen, Patti M. Valkenburg, and Patti M. Valkenburg. 2015. “Adolescents’ Comments in Social Media.” Computers in Human Behavior 53:486–94. doi: 10.1016/j.chb.2015.07.016.

Murayama, Taichi, Shoko Wakamiya, Eiji Aramaki, and Ryota Kobayashi. 2021. “Modeling the Spread of Fake News on Twitter.” PLOS ONE 16(4):e0250419. doi: 10.1371/journal.pone.0250419.

Nir Grinberg, Nir Grinberg, Nir Grinberg, Nir Grinberg, Kenneth Joseph, Kenneth Joseph, Kenneth Joseph, Lisa Friedland, Lisa Friedland, Briony Swire‐Thompson, Briony Swire-Thompson, Briony Swire-Thompson, David Lazer, and David Lazer. 2019. “Fake News on Twitter during the 2016 U.S. Presidential Election.” Science 363(6425):374–78. doi: 10.1126/science.aau2706.

Pennycook, Gordon, and David G. Rand. 2019. “Lazy, Not Biased: Susceptibility to Partisan Fake News Is Better Explained by Lack of Reasoning than by Motivated Reasoning.” Cognition 188:39–50. doi: 10.1016/j.cognition.2018.06.011.

Philippe Aussu. 2023. “Information Overload: Coping Mechanisms and Tools Impact.” Research Challenges in Information Science 661–69. doi: 10.1007/978-3-031-33080-3_49.

Roro Isyawati Permata Ganggi, Roro Isyawati Permata Ganggi, Roro Isyawati Permata Ganggi, and R. Isyawati Permata Ganggi. 2020. “Information Anxieties and Information Distrust: The Effects of Overload Information about COVID - 19.” E3S Web of Conferences 202:15014. doi: 10.1051/e3sconf/202020215014.

Sejeong Kwon, Sejeong Kwon, Meeyoung Cha, Meeyoung Cha, Kyomin Jung, Kyomin Jung, Wei Chen, Wei Chen, Yajun Wang, and Yajun Wang. 2013. “Prominent Features of Rumor Propagation in Online Social Media.” 1103–8. doi: 10.1109/icdm.2013.61.

Shao, Chengcheng, Giovanni Luca Ciampaglia, Alessandro Flammini, and Filippo Menczer. 2016. “Hoaxy: A Platform for Tracking Online Misinformation.” 745–50. doi: 10.1145/2872518.2890098.

Shao, Chengcheng, Giovanni Luca Ciampaglia, Onur Varol, Kai-Cheng Yang, Alessandro Flammini, and Filippo Menczer. 2018. “The Spread of Low-Credibility Content by Social Bots.” arXiv: Social and Information Networks. doi: 10.1038/s41467-018-06930-7.

Shin, Jieun, Lian Jian, Kevin Driscoll, and François Bar. 2018. “The Diffusion of Misinformation on Social Media: Temporal Pattern, Message, and Source.” Computers in Human Behavior 83:278–87. doi: 10.1016/j.chb.2018.02.008.

Tandoc, Edson. 2019. “The Facts of Fake News: A Research Review.” Sociology Compass 13. doi: 10.1111/soc4.12724.

Tandoc, Edson, Darren Lim, and Rich Ling. 2019. “Diffusion of Disinformation: How Social Media Users Respond to Fake News and Why.” Journalism 21:146488491986832. doi: 10.1177/1464884919868325.

Tim Hwang, and Tim Hwang. 2020. “Dealing with Disinformation: Evaluating the Case for Amendment of Section 230 of the Communications Decency Act.” 252–85. doi: 10.1017/9781108890960.012.

Vosoughi, Soroush, Deb Roy, and Sinan Aral. 2018. “The Spread of True and False News Online.” Science (New York, N.Y.) 359(6380):1146–51. doi: 10.1126/science.aap9559.

Ziva Kunda, and Ziva Kunda. 1990. “The Case for Motivated Reasoning.” Psychological Bulletin 108(3):480–98. doi: 10.1037/0033-2909.108.3.480.

Appendix: Cases of Scandal-diffusion model

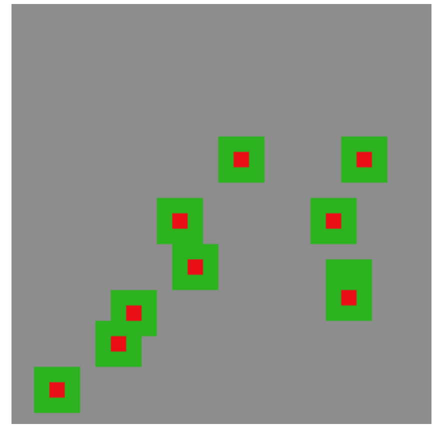


Figure 1. Extreme Case: Confucian Ideal of Society

Truth-cost = 50, Scandal-cost = 20.

Scandals = 10, probability-of-wises = 1.00, probability-of-rationales = 0.00.

In the ideal society of Chinese Confucianism, everyone is wise. Rumors are corrected immediately when diffused, truth prevalence.

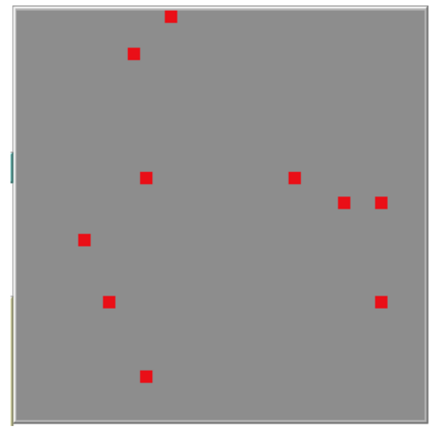


Figure 2. **Extreme Case: Babel Tower Society**

Truth-cost = 50, Scandal-cost = 20.

Scandals = 10, probability-of-wises = 0.00, probability-of-rationales = 1.00.

Everyone is indifferent to others and spreads nothing. Fake news cannot be diffused, while without communication, virtues also cannot be able to be exposed.

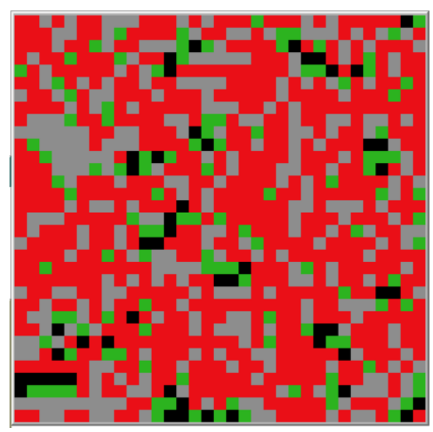
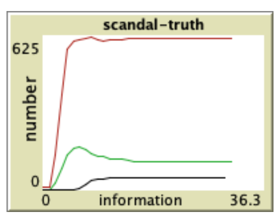


Figure 3. **World of Rumors**

Truth-cost = 50, Scandal-cost = 5.

Scandals = 10, probability-of-wises = 0.10, probability-of-rationales = 0.30.



The cost of correction is super high, and the cost of diffusing fake news is low. The number of people exposed to false information surged swiftly and soon remained around 625. The number of agents knowing the truth rises much slower initially but soon declines after the turning point of 168 and remains at the number of 103. Silent agents are around 29.

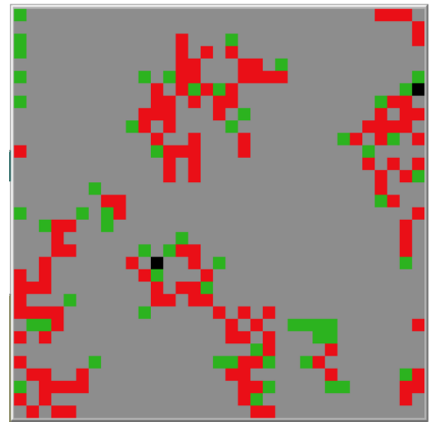
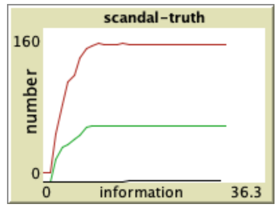


Figure 4. **Real-world**

Truth-cost = 20, Scandal-cost = 5.

Scandals = 10, probability-of-wises = 0.10,

probability-of-rationales = 0.70.



In the real world, only a small amount of people are exposed to fake news that brings bad outcomes. Only a very small amount of people would correct the misinformation. Still, fake news grows more quickly than truth but is much smaller in amount and becomes steady around 124. And the number of truths becomes steady around 38.

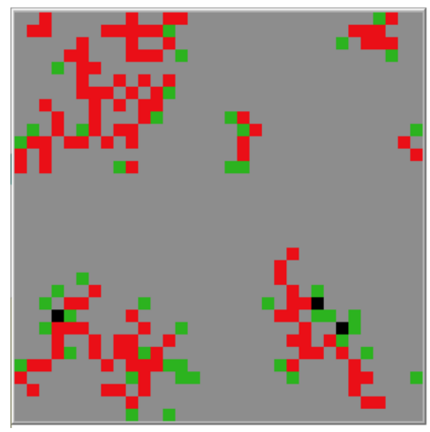
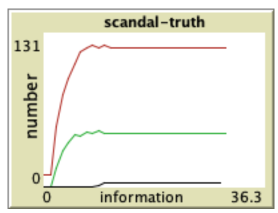


Figure 5. **Harsh Punishment**



Truth-cost = 20, Scandal-cost = 20.

Scandals = 10, probability-of-wises = 0.10,

probability-of-rationales = 0.70.

Nothing big change compared to the *Real-world* model.

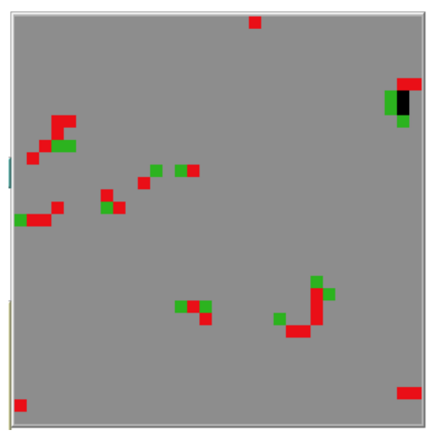
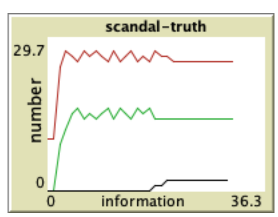


Figure 6. More **Rationales**

Truth-cost = 20, Scandal-cost = 5.

Scandals = 10, probability-of-wises = 0.10,

probability-of-rationales = 0.80.



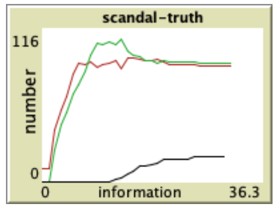
The number of rumors and truth fluctuate at the beginning and then becomes steady for scandals of 24 and truths of 13, which is much smaller than the real-world model.

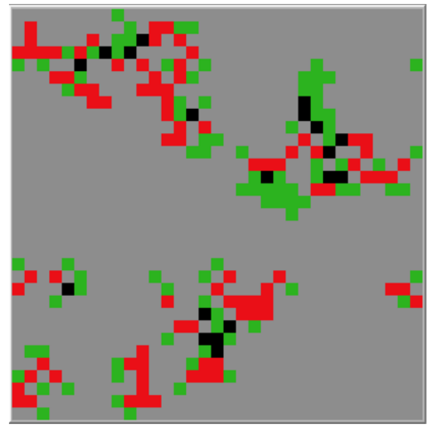
Figure 7. More Wise-a

Truth-cost = 20, Scandal-cost = 5.

Scandals = 10, probability-of-wises = 0.20,

probability-of-rationales = 0.70.





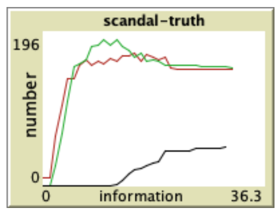
The number of rumors and truth surge almost simultaneously at the beginning and then becomes steady for scandals of 89 and truths of 87. False information rises higher initially but is soon exceeded by truths, and soon become similar in amount and reached steady status.

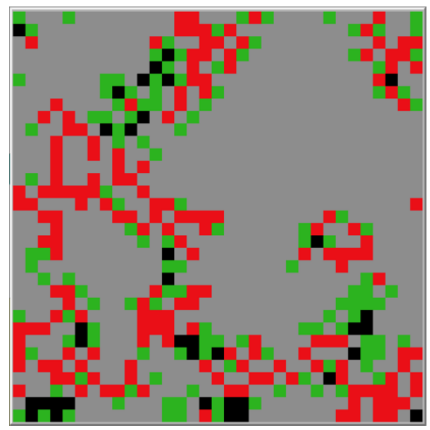
Figure 8. More Wise-b

Truth-cost = 20, Scandal-cost = 5.

Scandals = 10, probability-of-wises = 0.20,

probability-of-rationales = 0.60.





The number of rumors and truth surge almost simultaneously at the beginning and then becomes steady for scandals of 145 and truths of 150. False information rises higher initially but is soon exceeded by truths, and soon become similar in amount and reached steady status. Similar to Figure 7 but larger in scale.