The Domino Effect: TikTok Bot Echo Chambers

Team Members

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GitHub Repository: https://github.com/y8ahmed/eecs4461-project

Phenomena of interest: Summary

Our project will explore the phenomenon of Echo Chambers driven by social bots within modern media ecosystems, especially on Tiktok. In this scenario, AI-driven bots, configured to promote particular narratives, interact not only with human users but also with other AI bots. Over time, these automated agents reinforce and magnify each other's messages, creating self-sustaining information bubbles. This intensification leads to more polarized viewpoints, as users (human or bot) primarily encounter content that confirms their existing beliefs. By modeling such bot-to-bot interactions, we aim to illustrate how echo chambers can form and persist, even with minimal human oversight.

The echo chamber dynamic may be observed across social media platforms showing that automated echo chambers pose considerable challenges to information diversity and public discourse. For instance, Twitter (now known as X) bots have the potential to distort discourse formation through misrepresentation of data and this could be weaponized by malicious actors (Hartt et al., 2024).

Phenomenon of interest: Relevant Sources

The paper "The Spreading of Misinformation Online" describes the mechanisms through which false or misleading information propagates on digital platforms. The research highlights the influence of echo chambers and confirmation bias, emphasizing how misinformation can outpace verified information due to emotional engagement, virality, and algorithmic promotion. The paper also explores potential solutions, including fact-checking, improved digital literacy, and platform accountability, aiming to curb the societal and political impacts of misinformation proliferation.

The next paper examines how social media bots, like '*Urbanist Uma'*, influence online urban planning by creating echo chambers and amplifying specific viewpoints. While bots can distort public discourse and misrepresent community opinions, they also offer opportunities for planners to share information and engage diverse groups. The study highlights the need for responsible bot use and regulation in participatory planning.

This paper examines the echo chamber effects on short video platforms like Douyin, TikTok and Bilibili. It highlights how algorithms contribute to group polarization, reinforcing selective exposure and homophily among users. Using social network analysis, the study finds that Douyin and Bilibili exhibit strong echo chamber effects, while TikTok's global and culturally diverse user base appears to limit such polarization. The research suggests that echo chambers significantly impact information dissemination, potentially spreading misinformation, and discusses implications for platform management. [Note: new source added]

Sources listed below in order of paragraphs, I added a single new source at the bottom.

[1] 1. Del Vicario, M., Bessi, A., Zollo, F., Petroni, F., Scala, A., Caldarelli, G., Stanley, H. E., & Quattrociocchi, W. (2016). The spreading of misinformation online. Proceedings of the National Academy of Sciences, 113(3), 554–559. https://doi.org/10.1073/pnas.1517441113
[2] Hartt, M., Cantlay, S., Hollander, J. B., Potts, R., & Seto, A. (2024). iNIMBY? The potential of automated social media bots to create echo chambers in the online participatory planning discourse. International Planning Studies, 29(4), 436–448. https://doi.org/10.1080/13563475.2024.2433650
[3] Gao, Y., Liu, F., & Gao, L. (2023). Echo chamber effects on short video platforms. https://doi.org/10.1038/s41598-023-33370-1

Core Components of the Simulation

Social bots interact with one another and with humans on TikTok, to facilitate the formation of echo chambers. Below we categorize the various entities, affordances and algorithms relevant to simulating echo chamber formation and growth. We will draw on Mesa examples that are relevant to each component before specifying the closest in Section 4.

3.1 Entities

Our simulation will utilize human and bot agents, with bot agents having a higher number of interactions with other agents.

1. Human Agents
   Human agents may create content to be interacted with by other agents, or may mainly view, like, comment on, and share content. We do not distinguish between consumer and producer agents in this simulation for simplicity.

2. Bot Agents
   Bot agents mainly interact with content with the goal of boosting it. This includes:

   a. Amplifier Bots which boost content by interacting in large numbers;

b. Conversational Bots which drive discussion in comment sections; and,

c. Misinformation Bots which push false narratives through trending hashtags

We abstract the content a TikTok user interacts with as just the user interacting with the creator of that content. According to the Virus in a Network model, connections are the way an infection spreads. Likewise, a human agent interacting with a bot agent causes their network to become more similar, increasing the likelihood of another human agent interacting with the bot agent.

3.2 Affordances

Our simulation will focus on TikTok's recommendation algorithm and the affordances relevant to it. Affordances will be referred to as interactions in our simulation. The psychological characteristic of an interaction may be specified such that emotionally-charged interactions have a larger effect than neutral interactions. For instance, a fear-driven interaction draws an agent closer to the other to a greater degree than a neutral one.

Interaction Type	Interaction
Positive	Like View Comment Follow Share
Negative	Dislike Unfollow

Mesa Analogy: Schelling's Segregation Model. Just as individuals self-segregate based on similarity, positive interactions cause agents to cluster into ideological bubbles.

3.3 Algorithms

TikTok's recommendation algorithm prioritizes engagement-driven content, reinforcing echo chambers. Our simulation mimics this by simulating the dynamics of recommendations through human-bot agent interactions. Agents engage with one another based on proximity and probabilistic interactions*. Past interactions restrict content diversity, reinforcing ideological clusters. Bots take advantage of this and boost content to further their goals.

*Probabilistic interactions refer to the likelihood that an agent will do a positive or negative interaction, where positive interactions move agents closer and negative ones move them farther away. This will be determined by the ratio of positive to negative interactions we indicate.

Simulation Metrics

1. Engagement Clustering: Measures how tightly agents group around similar content.

2. Agent Interaction Rate: Tracks the speed of interaction between human to human, bot to bot and lastly bot to human.
3. Cross-Community Interaction: Evaluates exposure to agents from other clusters.

Mesa Analogy: Boid Flocking Model agents “flock” toward similar content over time, mimicking TikTok’s algorithm, where users cluster into echo chambers.

Simulation Anticipated Outcomes

The most similar Mesa example to our simulation is the Virus on a Network Model. We chose this for its potential to represent agents as nodes, interactions as edges, and the recommendation algorithm as a virus being passed between agents. However, we combine this with the Schelling Segregation Model by having the proximity of nodes change based on new interactions - interactions create an edge between nodes and they move closer to each other, eventually forming a cluster. This mimics TikTok’s recommendation of content based on a user’s history of content engagement. Hence echo chambers would be represented by clusters of nodes.

Before beginning the simulation, the following input parameters would be needed:

1. Number of human agents
2. Number of bot agents
3. Smallest cluster size
4. Initial Outbreak Size
5. Virus Spread Chance
6. Virus Check Frequency
7. Recovery Chance
8. Gain Resistance Chance
9. Randomized node density
10. Randomized node degrees

During the simulation, the following rules will apply to enable progression:

1. An agent with a degree of 0 will have a random positive interaction with another agent
2. Agents with a degree >0 will have a probabilistic interaction with a nearby agent
3. Each interaction will cause a change in agents’ proximity

The simulation will end when distinct clusters are formed. At the end of the simulation, we hope to measure:

1. Ratio of clusters to agents
2. Average distinct cluster size
3. Number of cross-cluster interactions
4. Number of steps to create clusters

The clusters will be shown on the graph, and the variables will be stated at the bottom of the graph. A 2D plot could be utilized to indicate the variable variation per step.

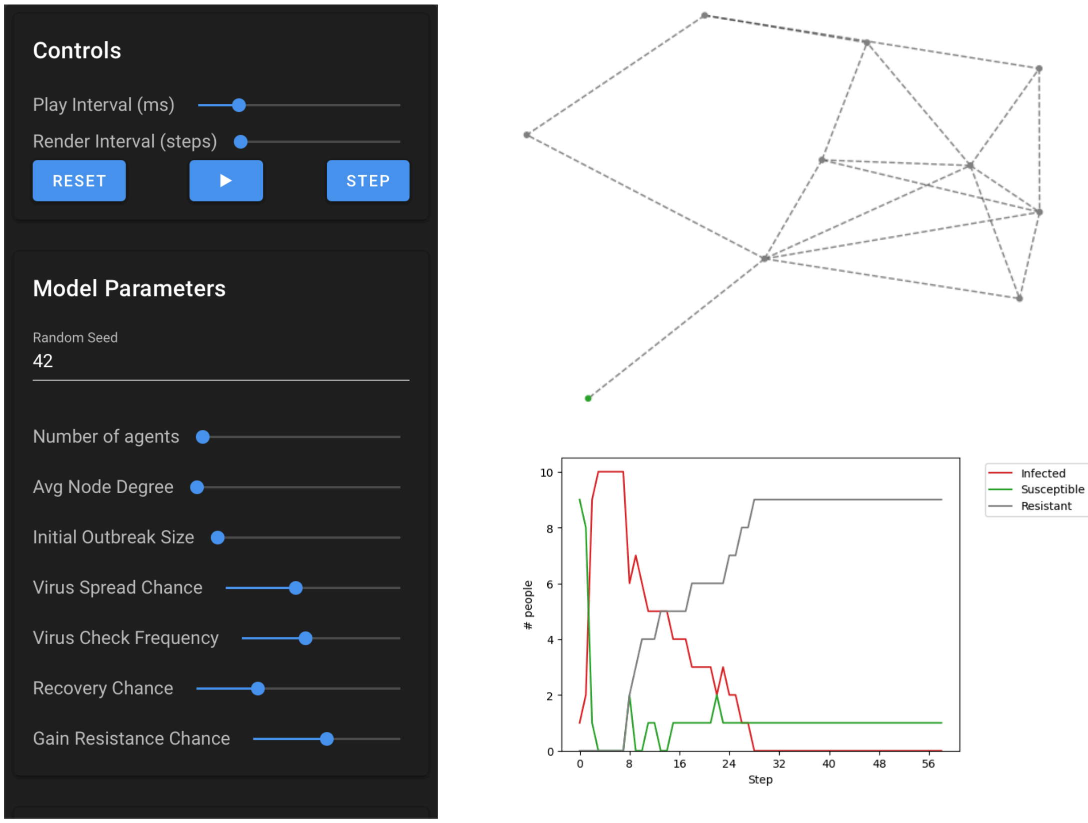

Figure 1: The Virus on a Network Model showing the input parameters, graph of agents, and plot of infected, susceptible and resistant nodes per step

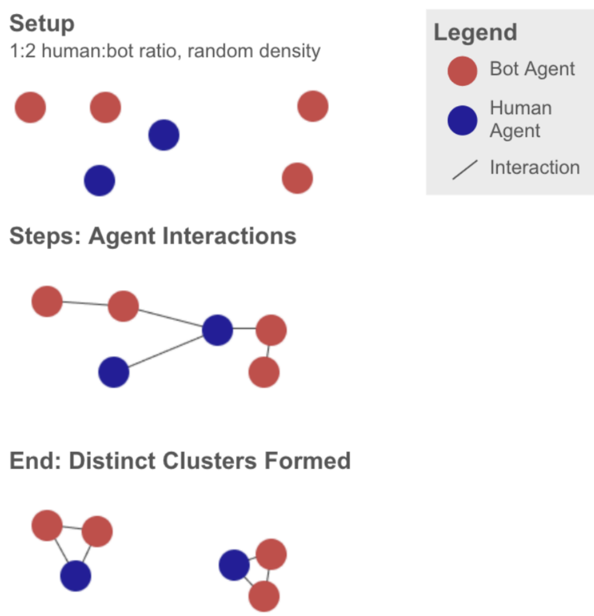

Figure 2: Preliminary Draft of our Echo Chamber Simulation

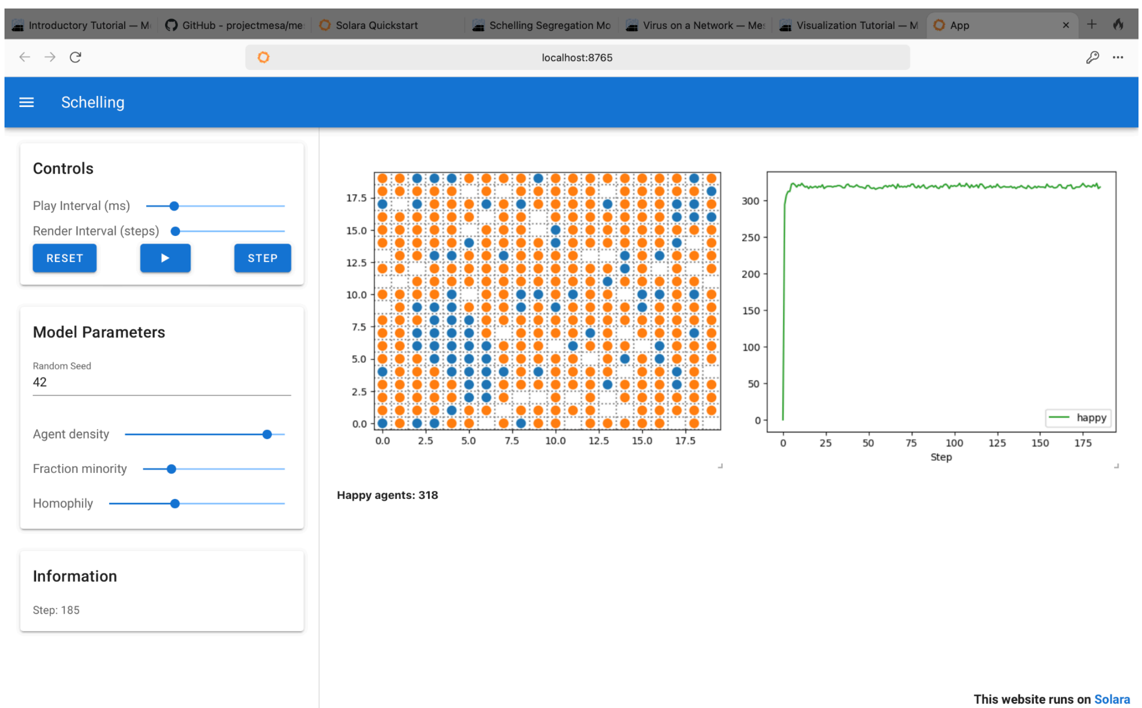

Figure 3: Screenshot of the Schelling Segregation Model