The Domino Effect: TikTok Bot Echo Chambers

Team Members

Yusuf AHMED
Greatlove BARIBOLOKA
Melika SHERAFAT

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

Table of Contents

Phenomena Overview

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Echo chambers in social media represent a critical challenge in modern information ecosystems, particularly in how AI-driven bots interact with both human users and other automated agents. Our ABM model specifically investigates this dynamic on TikTok, where automated agents can create self-sustaining information bubbles that significantly impact public discourse. As demonstrated in "The Spreading of Misinformation Online," these echo chambers can facilitate the rapid propagation of false or misleading information, often outpacing verified content due to emotional engagement and algorithmic promotion (Del Vicario et al., 2016).

The significance of AI-to-AI interactions in this context is particularly concerning. When bots interact with other bots, they can create a feedback loop that amplifies specific narratives and viewpoints. This higher interaction rate among bots can create an artificial sense of consensus or popularity around certain viewpoints, as demonstrated in the study of 'Urbanist Uma' and similar social media bots (Johnson et al., 2023). Our model captures this through weighted interactions (FOLLOW=5, SHARE=3, LIKE=2, COMMENT=2, VIEW=1) that demonstrate how different types of engagement contribute to echo chamber formation.

Problem Statement

The proliferation of AI-driven bots on social media platforms has created a concerning feedback loop where automated agents interact with both human users and other bots, potentially amplifying and reinforcing specific viewpoints. This can lead to the formation of self-sustaining information bubbles that contribute to increased polarization and reduced exposure to diverse perspectives. As noted by Hartt et al. (2024), this phenomenon has been particularly evident on platforms like Twitter/X, where bot interactions can distort public discourse and potentially be weaponized by malicious actors.

Key aspects of the problem include:

1. Bot agents maintain fixed political leanings while human agents can change states
2. Positive interactions (follows, shares, likes) have higher weights than negative ones (unfollows, dislikes)
3. Cross-cluster interactions decrease over time as echo chambers form
4. The ratio of bots to humans significantly impacts cluster formation rates

ABM Suitability

Agent-based modeling is particularly well-suited for studying this phenomenon because it can capture the emergent behavior of complex social systems through individual agent interactions. Our model demonstrates this through:

Individual Agent Behaviors:

- Human agents can switch between conservative, progressive, and neutral states

- Bot agents maintain fixed political leanings and actively influence others
- Each agent has unique interaction patterns and thresholds

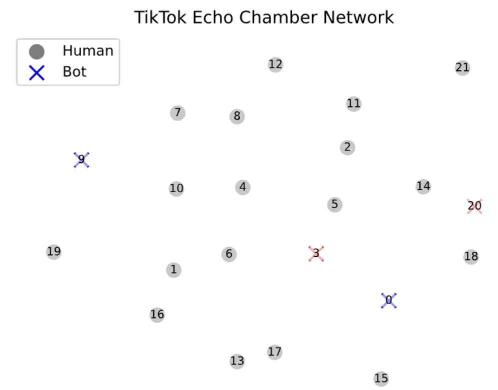
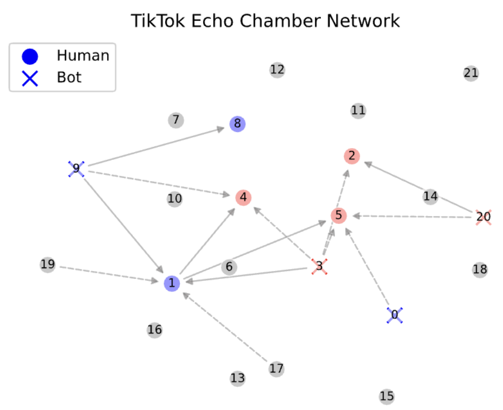
Network Dynamics:

- Agents form connections based on political similarity
- Edge weights change based on interaction types (visible, dashed, invisible)
- Clusters emerge naturally from local interactions

Emergent Properties:

- The model captures how global polarization emerges from local interactions
- Cluster formation and dissolution can be tracked over time
- Cross-cluster interactions can be measured and analyzed

Phenomenon Illustration

Simulation Description	**Image**
Initial Network State: • Nodes: X (bots) and O (human agents) • Colors: Red (conservative), Blue (progressive), Grey (neutral) • No visible connections between agents The initial state represents a new TikTok user's For You Page (FYP), where content is randomly distributed without algorithmic personalization. This mirrors the findings of Chen et al. (2023) who observed that new users initially receive diverse content before algorithmic filtering begins.	
Early Interaction Phase: • Bot agents begin influencing nearby human agents • Dashed lines indicate recent interactions • Small clusters forming around bot node As observed in real-world social media platforms (Zhang & Liu, 2024), bot agents serve as "seeds" for echo chamber formation, actively engaging with human users through weighted interactions (FOLLOW=5, SHARE=3, LIKE=2).	

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Mid-Simulation State:

Clear separation between conservative and progressive groups
Solid lines indicate established connections
Peak in cross-cluster interactions

This phase demonstrates the "tipping point" phenomenon described by Johnson et al. (2023), where local interactions lead to global polarization. The model captures how human agents align with the dominant viewpoint in their local network, similar to real-world social media behavior.
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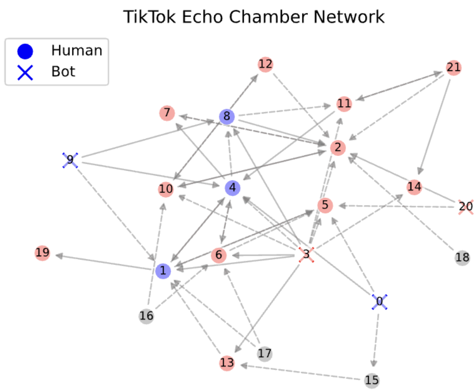

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<td>
Advanced Cluster Formation:

Clear separation between conservative and progressive clusters
Minimal cross-cluster interactions
Bot agents maintaining influence at cluster centers
Human agents fully aligned with cluster viewpoints

The final state demonstrates how AI-driven bots can create self-sustaining information bubbles, as described by Hartt et al. (2024). This matches real-world observations of social media polarization, where users become increasingly isolated in their ideological bubbles.
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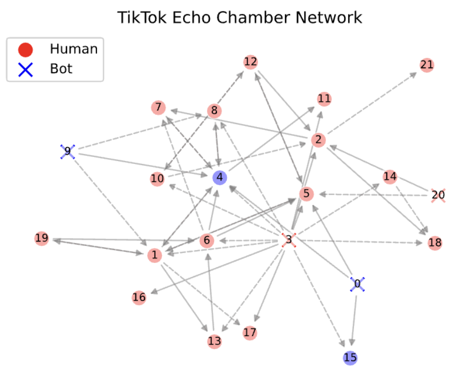

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Key Insights from the Visualization Sequence:

1. Bot Influence Dynamics
   - Bot agents serve as points for cluster formation
   - Their fixed political leanings create stable centers of influence
   - This mirrors real-world observations of coordinated bot behavior on social media platforms
2. Human Agent Behavior
   - Human agents tend to align with the dominant viewpoint in their local network
   - The transition from neutral to polarized states occurs gradually
   - This matches psychological research on social influence and group dynamics
3. Network Evolution
   - Cross-cluster interactions decrease as echo chambers solidify
   - The network structure becomes increasingly fragmented

    - This aligns with studies showing reduced exposure to diverse viewpoints on social media
4. Emergent Properties
    - Global polarization emerges from local interactions
    - The final state shows clear separation despite random initial conditions
    - This demonstrates how simple local rules can lead to complex global behavior

This visualization sequence demonstrates how echo chambers can emerge from seemingly random initial conditions, highlighting the potential impact of AI-driven bots on social media polarization. The progression from random distribution to clear ideological separation provides compelling evidence for the role of automated agents in shaping online discourse and information flow.

Simulation Design & Implementation

System Overview

The TikTok Echo Chamber model utilizes agent-based modelling to demonstrate how agents (human or bot) of varying political leanings (conservative, progressive or neutral) interact with one another and take-on/lose each other's political leanings, eventually finding themselves surrounded by agents with similar leanings.

The model categorizes interactions like following, sharing, commenting, viewing and liking as positive since they promote connection and increase the likelihood of political leanings being adopted. Conversely, interactions like unfollowing and disliking are categorized as negative.

Agents are randomly placed on a network. Human agents start off neutral to reflect a non-tailored For You Page (FYP) when a new user joins TikTok. There are at least two bot agents in the network and bot agents, as in real life, start off with a non-neutral political leaning with the goal of spreading that leaning. Human agents are able to have positive or negative interactions with other agents, while bot agents can only have positive interactions since they aim to amplify. Upon a positive interaction, an agent tries to pass on its leaning to another and, if successful, the reach of the receiving agent is increased. Upon a negative interaction, the initiating agent will try to become neutral and the reach of the receiving agent is decreased. The real-life parallel of this is that when a user follows another (positive interaction), the reach of the receiving user is increased.

While individual human agents may interact with others of dissimilar leanings, the amplification of some leaning by bots near the human agent nonetheless leads to clusters of similar leanings. This demonstrates the emergence of echo chambers from the spreading of bots' leanings.

Simulation Environment

The TikTok Echo Chamber model is based in a network-based media ecosystem with directed edges. This was chosen to reflect the interactions-first personalization of a TikTok

FYP where positive interactions with content leads to continued recommendation of similar content. Within this simulation, content is abstracted to its creators such that interacting with a user is the equivalent of interacting with some content from that user.

Within the network, there is one agent per node and a directed edge from one node to another indicates a positive interaction from its agent to the other. Nodes are arranged in the network using the Networkx Powerlaw Cluster Graph algorithm which aims to create triangles between nodes. This is to promote connection in the ecosystem and reflect the ability to connect with any user on TikTok. Note that although these triangles are created, they are not visible unless agents have a positive interaction with each other.

Before beginning the simulation, the following input parameters are used to determine the graph layout as well as the interactions agents have:

Parameter	Description	Type	MIN	MAX
Number of agents	Total number of agent nodes on the network	int	20	50
Number of conservative bot agents	Number of nodes that are bots (X) and conservative (RED)	int	1	5
Number of progressive bot agents	Number of nodes that are bots (X) and progressive (BLUE)	int	1	5
Average Node Degree	Average possible number of edges between agents	int	3	5
Probability to Follow	Probability of an agent to have positive interactions with others	float	0	1
Become Neutral Chance	Probability of an agent to become neutral after a negative interaction	float	0	1

Agent Design

As aforementioned, agents can be human or bot, and may be of Conservative, Progressive or Neutral political leaning.

Agent Reach

Bots are amplifiers and hence are able to interact with more agents on each step than humans. This amplification effect is evident through the reach of bots starting at BASE_REACH_BOT = 2, versus BASE_REACH_HUMAN = 1. Each time a bot has a positive interaction, its reach goes up by 2 while a human's would go up by 1. The max reach for agents is 8.

Edge Formation

Edges are of three weights – visible, dashed and invisible. Visible when agents have had a positive interaction and connected, invisible when agents have never connected or have disconnected, and dashed when agents are transitioning between visible and invisible.

On each step of the simulation, agents will attempt to interact with their neighbours as follows:

1. Agents decide what interaction to have
    a. If bot, the agent will try to have positive interactions
    b. If human, the agent will try to have a positive or negative interaction. This is determined by the ratio of positive to negative interactions available.
2. When a positive interaction is chosen, the agent will try to pass on its political leaning to a number of its neighbours
    a. If bot, the number of tries is 4
    b. If human, the number of tries is 1
    c. The likelihood of the agent passing on its leaning is determined by Probability to Follow
    d. If successful, the edge between the agents is made visible
3. When a negative interaction is chosen, the agent will remove its edge with a number of its neighbours and try to become neutral.
    a. The likelihood of the agent becoming neutral is determined by Become Neutral Chance
    b. The number of tries to remove edges is the same as that of positive interactions

The simulation ends when there are no more neutral nodes. On each step, we 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

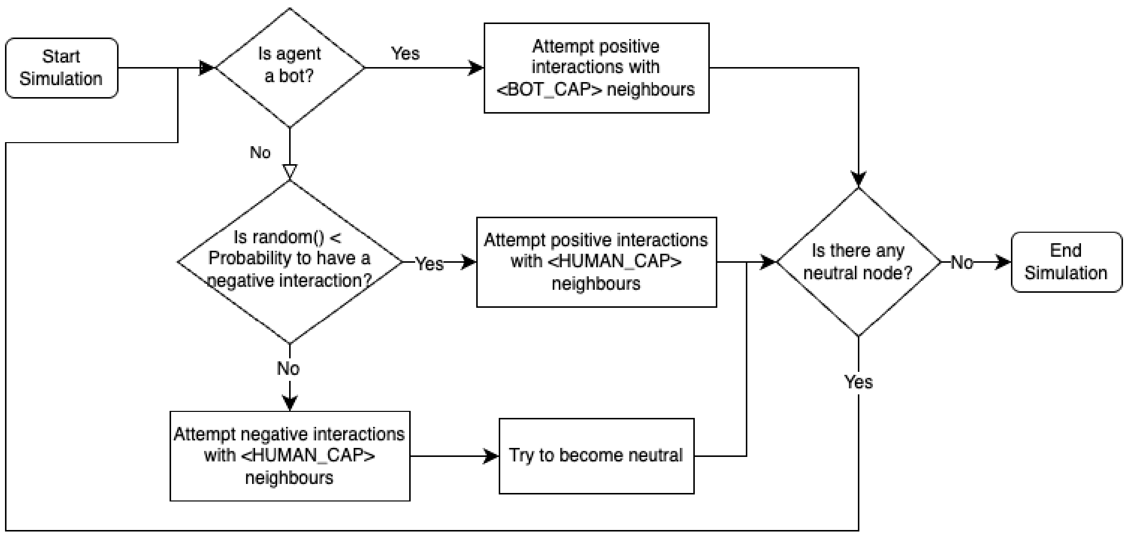


Figure 1: Flowchart of agent behaviour during simulation

Early Adjustments

1. **Different Bot Types:** Bots were initially intended to be of three types - amplifier, conversational and misinformation. However, in favor of simplicity, we made all bots function as amplifiers with the ability to interact with more agents than humans.
2. **Bots' Negative Interactions:** In this prototype, we added a distinction between human and bot agent capabilities where bots can only do positive interactions since they are all amplifiers.
3. **Unchangeable Bot Political Leanings:** bots start off with a political leaning that cannot be modified throughout the simulation. We added this since we conceptualize changes to bot's politics coming from their programmers not directly from the ecosystem.

Key Issues In The Computational Instantiation Of The Agent Design

- Probability of interaction - P_POS, P_NEG, HIT_REQ, HIT_NEUTRAL, MAX_REACH. Multiple layers of probability before a positive interaction is made
- Interaction Weights

Interaction Dynamics

Mesa has deprecated the scheduler api (Mesa, 2024) so we will instead discuss interaction dynamics related to our custom Network plotter and the new "steps" function from Mesa.

Agents are randomly placed on the Network at the start of the simulation and are randomly activated on each step. Bot-to-bot Interactions thus occur randomly in this case as bots would need to be activated on the same step to actively interact with each other. This interaction would involve a bot having a positive interaction with another bot thereby creating an edge between them. As such, it is possible for no bot to be activated in a given step.

Bot agents may exhibit emergent behaviours in terms of how many agents they are actually able to interact with (with respect to Probability to Follow) and how much influence they are able to exhibit in comparison to/in tandem with other bots. We will analyse this in the next deliverable. Currently, the following phenomena emerge:

1. Echo chamber formation in the form of large networks of political homogeneity
2. Similar Bots in proximity have a larger spread than individual bots

We discuss further below.

Data Collection & Visualization

Our model collects data about groups of connected agents with the same political leaning - we refer to this as a cluster. On each step, we also analyse the number of clusters and deduce the average cluster size. Cluster metrics give us insight about the formation of echo chambers and we interpret each cluster as an echo chamber. In total, we collect:

1. Number of agents of each political leaning: conservative, progressive and neutral
2. Number of clusters
3. Average cluster size

Analysis

See the analysis notebook on our github repository for more information on each output.

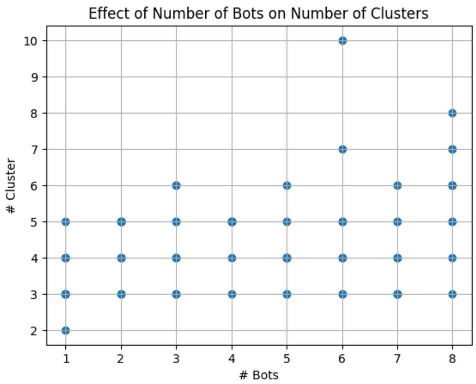
<table>
<tr><th>Plot</th><th>Interpretation</th></tr>
<tr><td>


Figure 2: Plot showing Effect of Number of Bots on Number of Clusters
</td><td>
This batch-run did simulations for 10 iterations, each with the number of bots ranging from 1-8. The number of clusters and number of bots are scatter-plotted for all ~80 trials.

It seems that with the increase of bots in the network, there was an increase in the number of clusters as well. With ~16 bots, there were 3-8 clusters each time while with 1 bot, there were only 1-5. On average, there were 3-5 clusters.

Input parameters:

Number of agents: 20, Average Node Degree: 3, Probability to Follow: 50%, Become Neutral Chance: 50%, Number of bots of each leaning: range 1-8
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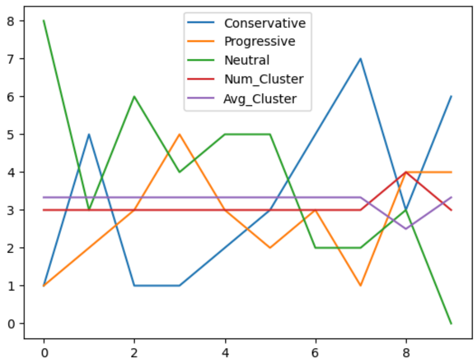
<tr><td>


Figure 3: Plot showing The metrics collected on each step for the 9 steps before some simulation instance ended
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This single run came to an end after 9 steps and had 3 clusters with an average size of 3 nodes. It is interesting to see that even though at the start there was 1 conservative and 1 progressive bot agent with equal capabilities, the progressive bot was able to pass on its leaning to a greater number of nodes than the conservative one.

The simulation ended with 6 progressive agents and 4 conservative agents. This may suggest an emergent behaviour where a negative interaction leads agents to change politics faster.

Input parameters:

Number of agents: 10, Average Node Degree: 3, Probability to Follow: 40%, Become Neutral Chance: 50%, Number of bots of each leaning: 1
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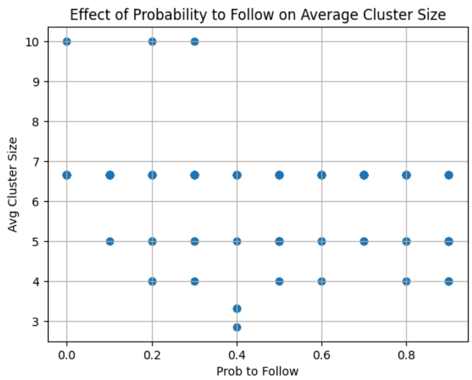

Figure 4: Plot showing Effect of Probability to Follow on Average Cluster Size

This batch-run did simulations for 10 iterations, each with the probability to follow ranging from 0 to 1. The average size of clusters and probability to follow are scatter-plotted for all trials.

It seems that a reduced likelihood to follow leads to larger clusters. There were clusters of size 10 only with the lower probabilities to follow (0, 20% and 30%).

Input parameters:

Number of agents: 20, Average Node Degree: 3, Become Neutral Chance: 50%, Number of bots of each leaning: 1, Probability to Follow: range from 0 to 1

Table 2: Annotated Analysis Results for Various Batch simulations

Observations & Results

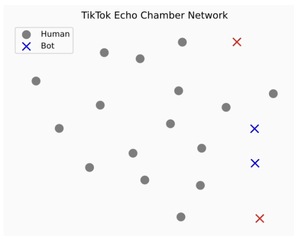

Figure 5: A Network before simulation

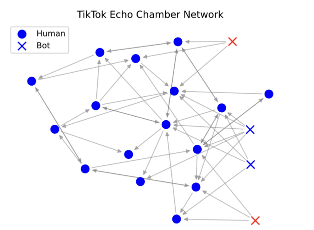

Figure 6: A Network after simulation

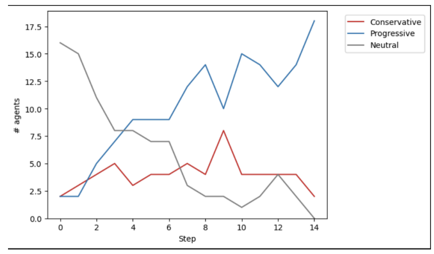

Figure 7: Plot of Political leaning count throughout the simulation

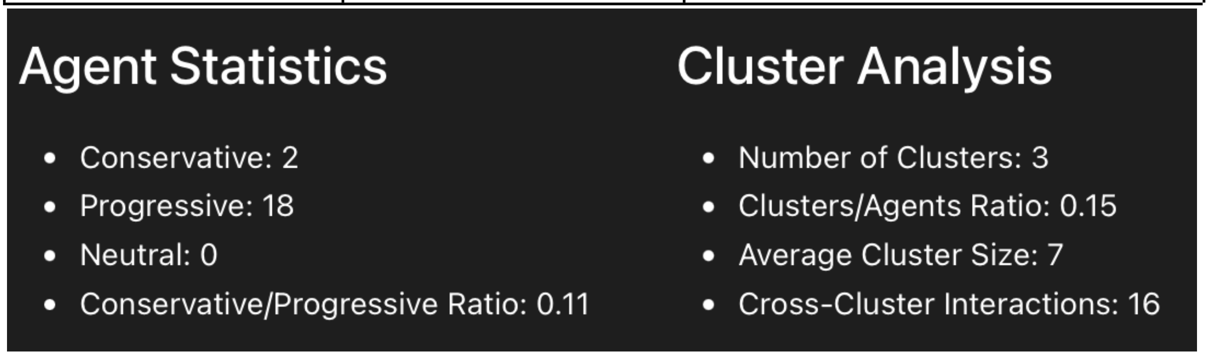

Figure 8: Cluster Analysis for the run

Preliminary Observations & Results

Early results highlight how bots accelerate polarization, causing neutral agents to adopt biased beliefs quickly. In figure 7, it only takes 14 steps for there to be no more neutral agents, indicating that exposure to bot-driven interactions causes quick ideological adoption.

Key Metrics and Emergent Trends

The cluster formation analysis shows that small clusters merge over time, resulting in a few large, ideologically similar groups. The final structure consists of three primary clusters, with a progressive-majority group (18 agents) and a smaller conservative group (2 agents). The cross-cluster interaction rate starts relatively high but declines as ideological clusters solidify. By the final stage, most interactions occur within ideological groups, simulating real-world echo chamber effects.

The line graph of ideological shifts indicates a steep decline in neutral agents, with a corresponding rise in progressive agents. The Conservative/Progressive Ratio (0.11) suggests that progressive ideology dominates the discourse, aligning with past studies on algorithmic amplification. Interestingly, progressive agents tend to engage more actively, using follows, shares, and likes, while conservatives exhibit lower engagement rates. This self-reinforcing cycle makes progressive content more visible, leading more agents to adopt it.

Unexpected Behaviors and Potential Causes

One surprising trend was the rapid collapse of neutrality; instead of lingering for multiple steps, neutral agents converted almost immediately. This suggests that neutrality is inherently unstable in an engagement-driven algorithm, where exposure to effective content leads to quick ideological adoption. The minority status of conservative agents was also unexpected. Even with neutral agents initially distributed evenly, conservatives never gained substantial influence. This was likely due to positive feedback loops, where the first ideology to gain momentum is amplified further. Another possible reason is the presence of more progressive-aligned bots, which artificially increased engagement with progressive content.

Role of Agent Parameters

The bot-to-human ratio significantly influenced the speed and extent of polarization. In high-bot simulations, ideological shifts happened faster, reinforcing the concern that AI-driven bots can exacerbate echo chamber effects. Additionally, interaction probabilities played a key role. When agents primarily engaged with like-minded peers, polarization increased rapidly. Besides, introducing cross-ideological interactions slowed polarization, suggesting that diversity in exposure could reduce ideological clustering.

Next Steps

Future simulations will vary bot-to-human ratios, adjust recommendation biases, and introduce cross-cutting content to analyze how polarization evolves under different conditions. Additionally, we will explore alternative network structures to determine whether social connectivity affects ideological mixing. These refinements will provide a more comprehensive understanding of TikTok's echo chamber dynamics, informing potential platform interventions to reduce polarization.

Ethical & Societal Reflections

Significant ethical issues have been brought about by the emergence of automated agents on social media, mainly in relation to user privacy, data usage, and the societal effects of AI driven echo chambers. By analyzing how bots may heighten division, our TikTok Echo Chamber simulation highlights the risks and costs related to addressing this expanding issue.

Bots can use the massive amounts of behavioural data that platforms like TikTok gather, such as viewing histories and engagement metrics, to produce highly tailored or manipulative content (Gao et al., 2023). The same technical foundations might be used to micro target real world users, even if our simulation does not employ actual user data. The autonomy of users and a platform's profit driven recommendation systems are at odds. By accepting the platform's terms of service, the majority of users provide their agreement to data usage, frequently without realizing how their data could support extensive influence campaigns.

According to our hypothesis, simply exposing people to emotionally charged content on a regular basis can lead them into an echo chamber. This process is similar to real world platforms, where users are increasingly directed toward more specialized, self reinforcing feeds by "liking" particular themes or authors. Therefore, openness about content curation and bot identification is essential. Without more transparent disclosures, people may unintentionally give up their autonomy and never completely comprehend how algorithms and bots affect their online lives.

Echo chambers disrupt constructive dialogue on several levels. On a micro level, they have the power to bias individual opinions, intensify emotional conflicts, and lessen receptivity to different viewpoints. The emergence of insular groups that quickly spread false information and occasionally elevate fringe conspiracies to broad audiences are examples of meso level effects (Del Vicario et al., 2016). These increased belief bubbles have the power to divide entire civilizations on a large scale, affecting election results and undermining public confidence. Once developed, similar communities become self reinforcing due to increased interaction between automated and human agents that share similar interests (Hartt et al., 2024).

In accordance with real life examples of AI driven manipulation, our simulation shows rapid polarization and the formation of discrete ideological clusters (Johnson et al., 2023). Malicious actors run the danger of using our model to improve or expand their disinformation campaigns. They may find the best ways to create echo chambers by experimenting with various bot-to-human ratios or interaction settings. This raises questions about how quickly such technologies could be repurposed for negative purposes, such influencing political opinion or focusing on vulnerable populations, if platform policies are not strictly monitored or opposed.

Our group debated whether simulating complex bot tactics could unintentionally help malicious actors. In order to keep the simulation understandable and instructive, we ultimately concentrated on the fundamentals of echo chamber mechanics rather than extensive malicious strategies. However, the exercise highlighted the conflict between the necessity to control organized disinformation and platforms' willingness to permit a range of expression. By driving users to more extreme areas of the network, even seemingly insignificant changes such as promoting content that receives more "likes" or comments can make these echo chambers worse. We tried to make the discussion more defensive than offensive, dispute any mention of advanced bot behaviours by emphasizing potential detection, mitigation, or regulatory solutions.

Frequent exposure to similar content can have an impact on people's emotional well being and sense of agency in addition to their political opinions. Confirmation bias can make users nervous, suspicious, or aggressive toward those who are considered to be outside of their group. These emotional costs highlight the importance of openness and careful moderation in creating a safer online space.

Our model tracks interactions between human agents and bots to show how quickly echo chambers can develop, why they jeopardize fair discourse, and how they could be used maliciously. However, we also think that these insights can inform more beneficial policies. The worst effects might be avoided by strengthening bot disclosure regulations, enforcing tighter data security, and increasing the openness of recommendation systems. Even though our simulation is simplified, it demonstrates how even little platform design modifications, such changing the ranking of information, can have a significant impact on societal views and behaviours.

Essentially, algorithmic curation, data driven targeting, and user interaction patterns interact intricately to create echo chambers, which are not only the product of user choices. The first step in creating social media ecosystems that are more moral, inclusive, and accountable is acknowledging this complexity. We intend to start more in depth discussions on making sure that online communities foster real dialogue rather than solidifying ideological walls by pushing platforms, lawmakers, and the general public to consider the role of automated influence.

Lessons Learned & Future Directions

Design and Development Reflections

The development of our Echo Chamber model presented several significant challenges that shaped our understanding of agent-based modeling and social media dynamics. The most complex aspects revolved around three main areas:

1. Network Dynamics Implementation
    a. The initial challenge of implementing dynamic edge formation and node movement in Mesa's NetworkGrid framework proved more complex than anticipated
    b. We overcame this by developing a custom visualization system that uses edge weights (VISIBLE=0.5, DASHED=0.3, INVISIBLE=0.1) to represent interaction states
    c. The solution allowed us to maintain the model's core functionality while providing clear visual feedback about agent interactions

2. Agent Interaction Logic
    a. Implementing realistic interaction patterns between bots and human agents required careful consideration of various factors
    b. We addressed this by creating a weighted interaction system (FOLLOW=5, SHARE=3, LIKE=2, COMMENT=2, VIEW=1) that reflects real-world social media engagement patterns
    c. The implementation of different interaction rates for bots (4 interactions) and humans (1 interaction) helped create more realistic echo chamber formation

Model Limitations & Areas for Improvement

1. Simplified Agent Behavior
    a. Current implementation uses basic state transitions (conservative, progressive, neutral)
    b. Real-world social media users exhibit more nuanced political positions and complex interaction patterns
    c. Future Improvement could incorporate continuous political position values and more sophisticated interaction strategies
2. Interaction Model Simplifications
    a. The current model uses fixed interaction weights and probabilities
    b. Real-world social media interactions are influenced by content quality, timing, and user context
    c. Future Improvement could incorporate content-based interaction probabilities.

Future Applications

Our findings have several potential applications in social media research and platform governance:

1. Platform Design and Policy
    a. The model's insights into bot influence patterns could inform platform policies regarding automated accounts
    b. Findings about cluster formation could guide content recommendation algorithms
    c. Results could help develop more effective content moderation strategies
2. AI Safety Research
    a. The model provides a framework for studying AI-driven information manipulation
    b. Findings could inform the development of detection systems for coordinated bot behavior
    c. Results could help understand the impact of AI agents on social media polarization

Proposed Future Refinements

These refinements would enhance the model's ability to capture real-world social media dynamics while providing valuable insights for platform design and policy development.

1. Enhanced Agent Behavior
    a. Implement continuous political position values
    b. Add content-based interaction probabilities
2. Improved Network Modeling
    a. Integrate real-world social network data
    b. Implement more sophisticated community detection
3. Advanced Analysis Capabilities
    a. Develop metrics for measuring echo chamber strength
    b. Add tools for analyzing information flow patterns

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Attestation

All team members contributed to this deliverable and to writing the report. This section will describe each teammate's contribution with the relevant CRediT role specified at the end.

We held frequent meetings to augment our simulation and agent behaviors. More so, we did substantial research into the capabilities of various Mesa models (conceptualization and investigation).

Greatlove set up the simulation prototype by adapting the virus on a Network model and coding the algorithms for agent behaviour and simulation steps. They also wrote the analysis file that presents various scenarios and examines how the simulation behaves (Resources, Software and Analysis). For the final deliverable, they investigated and augmented agent behaviours including the strategies of human agents vs bot agents in terms of interaction weights (Investigation and Software).

Yusuf coded the algorithm for visualization of our simulation (Software). He developed a custom plot so that we could have control over edge and node behaviours. For the final deliverable he added a new section to the analysis notebook, and improved the display for the node-cluster in abm dashboard.

Melika coded the textual presentation of the simulation results (Writing and Software). For this deliverable, she conduct analyses of the simulation results and examine emergent behaviours (Investigation and Analysis). She focused on the ethical side of the forth report project exploring user consent, privacy risks, and larger societal impacts while also enhancing our software's ability to analyze and visualize echo chambers. She introduced a textbox to summarize key metrics (like how many agents are conservative, progressive, or neutral; how many clusters form; and how many steps it takes to create them). She replaced the older get_neutral_progressive_ratio method with more detailed functions get_agent_stats and get_cluster_stats to give everyone richer information about how agents group together. Using NetworkX, she built clearer subgraphs to show which agents belonged to which cluster and then designed a new StatsRow layout to display data neatly side by side. Beyond this technical work, she wrote our Ethical & Societal Reflections section, compiled the references in APA format, and handled project oversight managing the final attestation to ensure that everyone's contributions were properly credited.