Unveiling the Truth and Facilitating Change: Towards Agent-based Large-scale Social Movement Simulation

Xinyi Mou¹, Zhongyu Wei^{1,2}*, Xuanjing Huang^{3,4}

¹School of Data Science, Fudan University, China ²Research Institute of Intelligent and Complex Systems, Fudan University, China ³School of Computer Science, Fudan University, China ⁴Shanghai Collaborative Innovation Center of Intelligent Visual Computing, China {xymou20, zywei, xjhuang}@fudan.edu.cn

Abstract

Social media has emerged as a cornerstone of social movements, wielding significant influence in driving societal change. Simulating the response of the public and forecasting the potential impact has become increasingly important. However, existing methods for simulating such phenomena encounter challenges concerning their efficacy and efficiency in capturing the behaviors of social movement participants. In this paper, we introduce a hybrid framework for social media user simulation, wherein users are categorized into two types. Core users are driven by Large Language Models, while numerous ordinary users are modeled by deductive agent-based models. We further construct a Twitter-like environment to replicate their response dynamics following trigger events. Subsequently, we develop a multi-faceted benchmark SoMoSiMu-Bench for evaluation and conduct comprehensive experiments across real-world datasets. Experimental results demonstrate the effectiveness and flexibility of our method.

1 Introduction

In the past decades, social media has witnessed many social movements, such as the Arab Spring (Rane and Salem, 2012) and #Metoo (Brünker et al., 2020). Twitter stands out as a prominent forum giving powerful voices to groups demanding change. As illustrated in Figure 1, the dissemination of breaking news on Twitter prompts the proliferation of opinions, influencing collective sentiment and shaping societal agendas, often resulting in real-world actions (Roy and Goldwasser, 2023). Although the majority of social movements are reported peaceful, the sheer scale of participation can sometimes escalate into violence and destruction, posing potential ramifications. Therefore, proactive measures to anticipate the impact of such events become imperative.

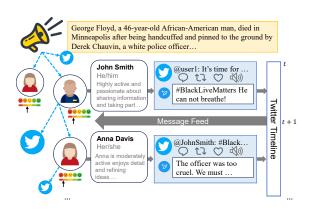


Figure 1: An illustration of user interactions and attitude changes after a trigger event happens. Users can take actions such as posting and retweeting according to their traits, and their generated content will be stored in the Twitter timeline and fed to their connected users. Users can change attitudes once perceive others' opinions.

Previous research on analyzing online social movements has primarily concentrated on retrospective analysis of content and users (Giorgi et al., 2022; Roy and Goldwasser, 2023), rather than utilizing simulation for prediction. Agent-based models (ABMs) have been extensively employed for simulation in social science (Schelling, 2006; Jackson et al., 2017), wherein each agent symbolizes an individual, and interactions among agents give rise to distinct social phenomena. Typically, ABMs are micro-level mathematical models that define how individuals affect each other, creating collective social patterns through simulating interaction at scale (Törnberg et al., 2023).

Recently, Large Language Models (LLMs) have demonstrated impressive ability in human-level intelligence (Wang et al., 2023b; Xi et al., 2023). LLM-based user simulations have been successfully experimented in domains such as recommendation (Wang et al., 2023c; Zhang et al., 2023) and collaborative work (Chen et al., 2023; Qian et al., 2023b). However, the exploration of conducting large-scale online social movement simu-

^{*}Corresponding author.

lations using LLMs remains limited and presents the following challenges: (1) How to accurately simulate users of social media and replicate their behaviors within the community? (2) How to efficiently simulate a large number of users, given the impracticality of employing thousands of LLMs? (3) How to comprehensively evaluate the effectiveness of the simulation?

To handle these challenges, this paper introduces a novel **hybrid framework for social media user simulation**. Considering the Pareto distribution ¹ inherent in social media user engagement, we categorize users into two types: core users, comprising active and influential figures such as opinion leaders, and ordinary users. Core users are characterized and driven by LLMs, enabling emulation of their complex behaviors, while a vast number of ordinary users are governed by ABMs, providing a practical way for user simulation in large scale.

Based on the hybrid mechanism composed of two types of users, we establish an online social media environment tailored for online social movement simulation and evaluation. In this environment, messages are organized in Twitter-like timelines and offline news can be disseminated. User interactions and resultant collective attitudes are observed through attitude scores. To systematically evaluate the simulation, we propose a novel benchmark SoMoSiMu-Bench, including three real-world collected datasets (Metoo, BlackLives-Matter and RoeOverturned) and an evaluation strategy at both the micro and macro levels, focusing on individual user alignment and systemic outcomes respectively. Evaluation results on SoMoSiMu-Bench demonstrate the effectiveness of our simulation framework.

Our contributions can be summarized as follows:

- We introduce a hybrid simulation framework where two types of users are separately modeled, to tackle the cost and efficiency challenges associated with simulating massive participants.
- We develop a simulator tailored for online social movements, featuring a Twitter-like environment and modeling of user opinion dynamics.
- We provide the first benchmark SoMoSiMu-Bench for social movement simulation evaluation, including a data collection consisting of three real-world movements and corresponding

evaluation methods. Experiment results and analysis demonstrate the effectiveness of our method.

2 Hybrid Framework for Social Media User Simulation

User engagement in social networks often exhibits a Pareto distribution, where the bulk of content originates from a small fraction of individuals. Thus, those more active and influential such as opinion leaders should be modeled finely, while the silent majority can be controlled by simpler models. The overall framework is illustrated in Figure 2, where social media users are divided into core users and ordinary users. The two types of users are driven by different models, to address the cost and efficiency issues of using thousands of LLMs.

2.1 Simulation of Core Users

We build an agent architecture by empowering LLMs with the necessary capabilities for core user simulation. An overview of the agent's architecture is illustrated in the left part of Figure 2. Empowered by LLMs, the agent is equipped with a profile module, a memory module, and an action module.

2.1.1 Profile Module

To pave the way for subsequent simulation and evaluation, we use real data for initialization. Each agent's profile contains the following content:

Demographics The basic profile is demographics, such as name, gender, race, political leaning and account type (Brünker et al., 2020). This information is highly related to the user's potential stance on social events. We induce the demographics from users' biographies and previous tweets.

Social Traits As participants in a social platform, agents' social traits such as activity and influence also capture important characteristics. Activity quantifies the frequency of a user's interaction, while influence reflects the quality and popularity of generated content. Since users exhibit long-tail distribution among these social traits, we segment them into three uneven tiers (Zhang et al., 2023).

Communication Roles To more accurately describe users in participation of social movements, we integrate Edelman's topology of influence (TOI) (Bentwood, 2008; Tinati et al., 2012) to identify the communication roles of online users: (1) **Idea Starter**: individuals who start the conversation and

¹https://en.wikipedia.org/wiki/Pareto_
distribution

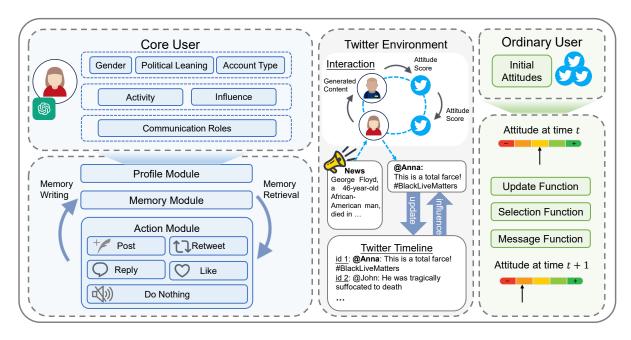


Figure 2: The proposed framework architecture. The left part shows the architecture of LLM-empowered generative agents for core user simulation. The right part presents the mechanism for deductive agents for the opinion dynamics of ordinary users. The initial status of users is determined by real Twitter data. At each round, core user agents take actions based on contextual information, and their attitudes are conveyed to ordinary users after sentiment analysis.

post original content. (2) **Amplifier**: users who collect multiple thoughts and share ideas and opinions. (3) **Curator**: they use a broader context to define ideas. They tend to take the ideas of others and either validate, question, challenge or dismiss them. (4) **Commentator**: users who take part in something to which they strongly feel about. They retweet actively. (5) **Viewer**: the inactive majority, who prefer to consume information rather than create or share information online.

2.1.2 Memory Module

We integrate a memory module to manipulate memories of agents, mainly including three operations:

Memory Writing The raw observations including behaviors performed by the agents themselves or tweets visible to the agents, are first input into the memory module, in both forms of natural languages and vector representations.

Memory Retrieval Agents extract information from the memories that are relevant to the current observation. The retrieval function gets observations based *recency*, *importance* and *relevance* (Park et al., 2023). The top-ranked memories are subsequently integrated as part of the prompt.

Memory Reflection We incorporate the reflection operation to urge the agents to generate high-

level thoughts. We follow Park et al. to implement reflection periodically, with steps including: (1) identifying the most salient questions that can be asked given the agent's recent experiences; (2) prompting agents to extract high-level insights. This type of memory will be included alongside other observations when retrieval occurs.

2.1.3 Action Module

We design an action module tailored for social media ecology, where actions are highly related to information and attitude propagation, including: (1) **Post**: post original content; (2) **Retweet**: retweet an existing tweet in the agent's page, either forward directly or post additional statements; (3) **Reply**: reply to authors of existing tweets or replies; (4) **Like**: like an existing tweet in the agent's page; (5) **Do Nothing**: do nothing and keep silent.

2.2 Simulation of Ordinary Users

We use deductive ABMs to simulate ordinary users. Although a wide variety of ABMs have been proposed, they can be viewed as a unified formulation (Chuang and Rogers, 2023), where three key functions can specify it, i.e., the *attitude update function* f_{update} , the *selection function* $f_{selection}$ and the *message function* $f_{message}$.

2.2.1 Update Function

The update function generally defines the change of attitudes. Formally, the attitude update is:

$$\Delta a_{i,t} = a_{i,t+1} - a_{i,t} = f_{\text{update}} (a_{i,t}, M_{i,t}),$$
 (1)

where $\Delta a_{i,t}$ is the attitude change of agent i from time step t to t+1, $a_{i,t}$ and $a_{i,t+1}$ are the attitude of agent i before and after interaction, and $M_{i,t} = \{m_{j,t} \mid j \in J_{i,t}\}$ are the messages the agent i receive from $J_{i,t}$, i.e., those who interact with the agent i at time step t.

In practice, the update function can be formulated differently to account for the combined influences of the assimilation force (DeGroot, 1974), reinforcement force (Hunter et al., 2014), similarity bias (Rainer and Krause, 2002) and repulsion force (Jager and Amblard, 2005).

2.2.2 Selection Function

The selection function determines the set of agents $J_{i,t}$ that will have a social influence on agent i. It can be driven by internal factors like internal intendancy to interact with those more similar to them, or by external factors such as recommendation algorithms of the platforms.

2.2.3 Message Function

The message function determines the message $m_{j,t}$ that agent j shares based on its attitude $a_{j,t}$. Formally, the message function is:

$$m_{j,t} = f_{\text{message}} \left(a_{j,t} \right), \tag{2}$$

Most ABMs assume that agents convey their internal attitude with other agents without bias, i.e., $m_{j,t} = f_{\text{message}}(a_{j,t}) = a_{j,t}$.

We include several deductive ABMs with different function implementations, such as the Bounded Confidence Model (Deffuant et al., 2000) and the Social Judgement Model (Jager and Amblard, 2005), as foundations to simulate ordinary users.

2.3 Interaction between Agents

In the hybrid system, the influence between different agents is shown in the center of Figure 2. Considering that the impact of ordinary users on core users is subtle, we currently do not address the influence from ordinary users to core users.

Core User to Core User Core users convey their thoughts to others by generating specific tweet content, in the form of natural language sentences. As part of the prompt for some other core users, it influences the generation of the agents.

Core User to Ordinary User To transform the content generated by core users into acceptable inputs for ABMs, we calculate the attitude score. External LLMs are employed to annotate the stance, i.e., attitude direction of the content, and sentiment analysis tool ² is further applied to calculate the attitude intensity. After that, the scores can be processed by the message function in ABMs.

Ordinary User to Ordinary User Information is transmitted among ordinary users according to the message function in ABMs.

3 Simulation Platform

To simulate and evaluate users' reactions during real events, we build a Twitter-like simulation platform that the agents are situated within and discuss the execution of the simulation.

3.1 Online Social Media Environment

Firstly, we construct a twin environment of Twitter, to replicate the authentic online social environment.

3.1.1 Message Feed Mechanism

The environment operates based on the concept of timeline (Tinati et al., 2012). In this environment, each user has a timeline of tweets created by themselves and other users they follow. Also, a public timeline is kept to store tweets sent by all users. At each round, the most recent tweets visible to agents are provided as context for prompting.

3.1.2 Offline News Feed

Some offline events often act as catalysts for social movements, such as the George Floyd incident triggering the widespread #BlackLivesMatter movement. Therefore, we provide real-world events described in natural languages as background information to the agents for core users.

3.2 Task Formulation

To facilitate subsequent quantitative evaluation of the results, we abstracted the simulation into the following task. We consider a group of users $\mathcal{U}=\{1,\ldots,U\}$, each of whom participates in an online social movement and has an attitude on the specific topic. The attitudes evolve through social interaction. Let $a_{i,t}\in\mathbb{A}=[-1,1]$ be the attitude that user i holds at time step $t\in\{1,2,\ldots\}=\mathbb{N}$, where the sign of $a_{i,t}$ entails the direction of the attitude and the absolute value of $a_{i,t}$ represents

²https://github.com/sloria/TextBlob

Dataset	Event	#Users	#Tweets	Time Span
Metoo	E1	1,000	18,638	Oct 15 - Oct 22, 2017
	E2	1,000	13,291	Jan 06 - Jan 13, 2018
Roe	E1	1,000	61,687	May 02 - May 09, 2022
	E2	1,000	59,829	Jun 24 - Jul 01, 2022
BLM	P1	1,000	10,710	May 25 - Jun 01, 2020
	P2	1,000	21,480	Jun 02 - Jun 09, 2020

Table 1: Statistics of our dataset. In Metoo, E1 is American actress Alyssa Milano starts the #Metoo movement and E2 is #Timesup campaign on the 2019 Golden Globes Awards; In Roe, E1 is The leakage of the Supreme Court draft opinion and E2 is The Supreme Court overturns Roe v. Wade; In BLM, we include two phases after the Murder of George Floyd.

the magnitude of the attitude. For each user, we instantiate the corresponding agent with the user's initial attitude and available profile. Then, we aim to (1) simulate the behaviors of each core user at the micro level given a certain context; (2) simulate continuously to calculate the systemic outcomes resulting from user interactions at the macro level, namely the attitude distribution and changes.

3.3 Simulation Process

Our simulator operates in a round-by-round manner. During each round, i.e., time step, agents for core users autonomously give a thought before taking actions and then decide what actions they would like to take. Overall, LLM agents for core users perform actions based on the following information: (1) profile or description of the agent itself; (2) memory of the agent; (3) triggering offline news, if events happen; (4) the tweet page showing tweets visible to the agent; (5) notifications containing replies to the agent. Agents for ordinary users update their attitudes based on the pre-defined mechanism in ABMs and perceived messages from other agents.

4 SoMoSiMu-Bench: A Benchmark for Social Movement Simulation

In this section, we present the **SoMoSiMu-Bench**, a benchmark for simulation evaluation. We construct a data collection, composed of three social movements on Twitter. Then, evaluation strategies at the micro and macro levels are designed.

4.1 Datasets

We first present the construction of our dataset.

Data Collection To broadly evaluate the simulation performance of the proposed method, we

construct a Twitter data collection by collecting tweets related to specific social movements, i.e., *Metoo* (Maiorana et al., 2020), *RoeOverturned* (*Roe*) (Chang et al., 2023) and *BlackLivesMatter* (*BLM*) (Giorgi et al., 2022). For each movement, we collect tweets spanning two specific events or phases, as outlined in Table 1.

User Selection Due to the absence of an authoritative definition for core users, we identify core users by ranking all participants based on the activity and influence metrics in practice. From the gathered tweets, we select 300 core users by first identifying the top 100 most influential individuals based on the number of received retweets. We then extend this selection by selecting an additional 200 active users from their social networks, based on their overall tweet frequency. Next, we randomly sample ordinary users from those who tweeted during the event period. Subsequently, we collect their social networks and tweets during the period and annotate the attitude scores using GPT-3.5 (OpenAI, 2023) and Textblob.

To reduce the annotation cost for validation, rather than the simulation cost, we retain 700 ordinary users. As a result, 1,000 users are acquired for the simulation of each event. The statistics of the datasets are presented in Table 1. More details can be found in Appendix A.

4.2 Micro Alignment Evaluation

To evaluate the effectiveness of the simulation at the micro level, we simulate in single rounds by providing authentic contextual information to each core user agent and assess their decision-making.

- Stance Alignment: We evaluate the stance of generated content, i.e., classify it into three categories: *support*, *neutral* and *oppose*. Accuracy and F1-scores are reported.
- Content Alignment: We classify the agentgenerated content into 5 types, i.e., Call for Action, Sharing of Opinion, Reference to a Third Party, Testimony and Other (Brünker et al., 2020). Accuracy, and F1-scores are reported, and cosine similarity between simulated content and real content is also provided.
- Behavior Alignment: We evaluate whether the agents take the corresponding actions done by users. Since only posting and retweeting can be observed in Twitter datasets, we narrow down the action space to post and retweet. Accuracy and F1-scores are reported.

Datasets	Stance				Con	itent	Behavior			
	Acc.	MiF	MaF	Acc.	MiF	MaF	Sim.	Acc.	MiF	MaF
Metoo	0.8016	0.8016	0.3394	0.8520	0.8520	0.1533	0.6847	0.7563	0.7563	0.4870
Roe	0.7070	0.7070	0.3260	0.9756	0.9756	0.1975	0.7254	0.7688	0.7688	0.5375
BLM	0.6810	0.6810	0.5301	0.9209	0.9209	0.1598	0.6699	0.7908	0.7908	0.5431

Table 2: Results of micro alignment evaluation.

Method	Metoo				Roe				BLM			
	$\Delta_{Bias}\downarrow$	$\Delta_{Div.} \downarrow$	$\mathrm{DTW}{\downarrow}$	Corr.↑	$\Delta_{Bias}\downarrow$	$\Delta_{Div.} \downarrow$	$\mathrm{DTW}{\downarrow}$	Corr.↑	$\Delta_{Bias}\downarrow$	$\Delta_{Div.} \downarrow$	$\text{DTW}{\downarrow}$	Corr.↑
BC	0.0124	0.0184	2.7760	0.4831	0.0265	0.0144	5.7662	-0.7755	0.0078	0.0036	5.2289	-0.4404
Hybrid w/ BC	0.0135	0.0108	1.8440	0.7043	0.0239	0.0121	2.4611	0.3607	0.0300	0.0069	3.9254	0.1248
HK	0.0093	0.0105	2.9171	0.0262	0.0258	0.0185	7.7254	-0.7532	0.0081	0.0101	4.1204	-0.3026
Hybrid w/ HK	0.0126	0.0037	1.9136	0.6517	0.0319	0.0157	3.6752	-0.0807	0.0578	0.0093	3.7288	-0.2433
RA	0.0062	0.0055	3.1063	-0.0687	0.0237	0.0120	2.9521	0.0811	0.0039	0.0017	3.0441	0.2666
Hybrid w/ RA	0.0117	0.0008	1.7829	0.7238	0.0221	0.0104	2.3326	0.4274	0.0376	0.0070	2.2353	0.6050
SJ	0.0064	0.0192	2.2994	0.2009	0.0209	0.0106	1.2739	0.6177	0.0411	0.0072	2.7778	0.4475
Hybrid w/ SJ	0.0098	0.0119	2.2789	0.6327	0.0203	0.0095	1.1896	0.6598	0.0076	0.0018	2.4564	0.5167
Lorenz	0.0131	0.0198	5.3049	-0.4657	0.0352	0.0172	1.1027	0.7329	0.0895	0.0094	2.8897	0.4387
Hybrid w/ Lorenz	0.0035	0.0116	2.9857	0.6103	0.0093	0.0147	1.0148	0.7576	0.0023	0.0079	2.5394	0.5055

Table 3: Results of macro system evaluation. The average results of 3 runs are reported. In the vast majority of cases, hybrid systems show improvements across various aspects compared to ABMs. **Bold** presents the best performance in the column. <u>Underline</u> indicates the metric for the hybrid model did not surpass that of the corresponding ABM.

4.3 Macro System Evaluation

To evaluate the effectiveness of the simulation at the macro level, we quantify the attitude distribution from both horizontal and vertical perspectives in a complete multi-round simulation.

- Static Attitude Distribution: We capture characteristics of attitude distribution in quantitative terms: Bias and Diversity (Lorenz et al., 2021). Bias is measured as the deviation of the mean attitude from the neutral attitude, and Diversity is the standard deviation of attitudes. We measure at every time step and average over time. Differences between simulated and real measures $\Delta Bias$ and ΔDiv . are reported.
- Time Series of the Average Attitude: We measure the similarity between the time series of average attitude and the simulated one, using Dynamic Time Warping (DTW) (Müller, 2007) and Pearson correlation coefficient (Cohen et al., 2009).

Calibration and Validation To find the proper parameters for ABMs in the hybrid system, we perform the calibration and validation settings (Gestefeld and Lorenz, 2023). Calibration aims to find the best combination of parameters that can help match the empirical distributions. We specify parameter values for a parameter sweep to produce simulation results on E1 or P1 of each movement. Then, we

report the validation results on E2 or P2. Since simulating with LLMs hundreds of times is unaffordable, we perform calibration in pure ABMs and apply the optimal parameters to the hybrid model. The details can be found in Appendix B.

5 Experiments

5.1 Experiment Settings

We incorporate the following ABMs for ordinary users in the hybrid framework. Meanwhile, we employ these ABMs to model all users (referred to as pure ABMs) as baselines for comparison. More details can be found in Appendix B.

- Bounded Confidence Model (BC) (Deffuant et al., 2000): it assumes that if the received message is close enough to an agent's attitude, the message has an assimilation force on the agent.
- Bounded Confidence Model-Multiple (HK) (Rainer and Krause, 2002): a variant of BC, which can handle multiple sources.
- Relative Agreement Model (RA) (Deffuant et al., 2002): extends the BC in that the similarity bias is a continuously decaying function.
- Social Judgement Model (SJ) (Jager and Amblard, 2005): additionally includes a repulsion force based on BC.

- Lorenz (Lorenz et al., 2021): includes assimilation force, reinforcement force, similarity bias, polarization factor and source credibility.

5.2 Micro Alignment Evaluation

Table 2 shows the results of the micro alignment evaluation on the three datasets. We can observe:

- LLM-empowered agents effectively model core users' stance on specific topics, achieving over 70% accuracy. This can be attributed to the personalized profiles reflecting users' leanings. However, they struggle to generate neutral content, resulting in low MaF scores. This is because LLMs tend to produce content with clear stances, unlike real users who may share neutral information like external links or mentions.
- The LLM-empowered agents can replicate the types of content generated by users. Both in the real data and simulated results, user-generated content tends to be concentrated in *call for action* and *sharing of opinions*. Moreover, the overall cosine similarity between real and simulated content approaches 70%, affirming their capability to replicate user responses to specific contexts.
- The LLM-empowered agents can well distinguish between different users who are more inclined to create original content and those who prefer to retweet, achieving over 75% accuracy on all the three datasets. It can be attributed to the portrayal of communication roles in the profile, which indirectly influences the agents' choice of actions in the Twitter environment.

5.3 Macro System Evaluation

Table 3 shows the results of the macro system evaluation. We can observe:

- Overall, the hybrid models outperform pure ABMs in terms of both static measures and time series measures. Among the models, those based on the RA and Lorenz demonstrate advantages across various datasets, benefiting from the ability of RA and Lorenz in modeling situations of extremism (Chuang and Rogers, 2023).
- Hybrid models usually exhibit higher attitude bias compared with the corresponding pure ABMs. It's also the result of the LLMs' leaning to generate content with clear stances. With more agents modeled as positive, the overall level of attitude is also overestimated.

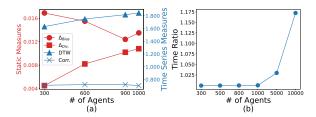


Figure 3: (a) System metrics when simulating with varying numbers of agents (better viewed in color); (b) Running Efficiency with varying numbers of agents.

Taking advantage of the accurate replication of attitudes of core users empowered by LLMs, even when pure ABMs fail to capture the overall trend in attitude changes, the overall trend can be corrected in the hybrid models under the guidance of these powerful LLM-based agents.

5.4 Efficiency Analysis

Figure 3 depicts the performance and runtime variations observed in the Metoo experiment across different numbers of agents. For comparative analysis, we establish the real distribution of 1,000 agents in Sec 5.3 as the reference and assess the performance of hybrid models featuring 300 core users alongside varying numbers of ordinary users. In Figure 3a, except for Δ_{Bias} , all other metrics exhibit a slight decline as the proportion of ordinary users increases. Figure 3b illustrates the simulation time ratio with varying numbers of agents relative to the time in the main experiment with 1,000 agents, where the core users remain fixed at 300. Notably, the runtime primarily depends on the time required for LLM API key invocation, with scaling up the number of ordinary users hardly imposing any additional burden. This observation underscores the scalability of our method.

5.5 Further Analysis

We further discuss more details about the simulation of the LLM-empowered core users, offering insights to enhance community communication.

5.5.1 Echo Chambers

We aim to assess whether the simulation can replicate the echo chamber, a common phenomenon in online social networks. We explore this question from the perspective of the consumption and production of content (Garimella et al., 2018). The content of production is the content generated by the agents, while the content of consumption is that generated by agents they "follow". The similarity

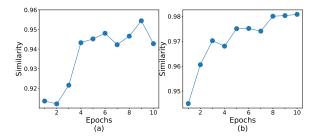


Figure 4: (a) Similarity of content of consumption and production on *Metoo* simulation; (b) Similarity of content of consumption and production on *Roe* simulation. *BLM* is not reported since it is a partial phrase rather than an event.

Method	Avg. Homogeneity	Avg. Toxity
S1	0.8551	0.1426
S2	0.8580	0.1296
S3	0.8962	0.1163

Table 4: Results of solutions to break the echo chambers. **Bold** presents the best performance in the column.

between production and consumption indicates the users' tendency to consume content that is similar to their own. Figure 4 reveals that as the number of epochs increases, the average similarity shows an overall upward trend for both datasets. These results further validate the system's capability to reflect the echo chambers.

5.5.2 Break the Echo Chambers

Given that echo chambers often contribute to polarization, we aim to explore strategies to mitigate this effect while safeguarding users' freedom of expression. We propose and test three solutions in our simulation framework: S1 - Feeding the opposite opinions; S2 - Feeding the neutral opinions; S3 -Establishing public spaces for debate or discussion, achieved by encouraging users to share opinions using platform-provided public hashtags. We experiment on the Metoo dataset and evaluate the homogeneity and toxicity of different situations. The homogeneity is measured by the method in Sec 5.5.1 and the toxicity is measured using the Perspective API ³. Table 4 illustrates that all three approaches can reduce the echo chambers, but the introduction of opposing opinions can increase the toxicity of the community, while establishing spaces for open discussion can promote more peaceful exchanges.

6 Related Work

6.1 LLM-empowered Autonomous Agents

With the prominent development of Large Language Models, the LLM-empowered autonomous agent has recently gained significant attention. Integrating profile, memory, reflection and planning modules, Park et al. design generative agents to simulate the human daily life. Based on this universal framework, agents with slightly different architectures have been widely applied in various scenarios and applications. Among these works, some are utilized for task-solving purposes, i.e., executing pre-defined tasks, such as software development (Qian et al., 2023a,b; Hong et al., 2023), collaboration (Chen et al., 2023), and exploring the world in Minecraft (Wang et al., 2023a). Others focus on simulation, where the replication of human behaviors is focused. Scenarios including social interaction, (Park et al., 2022; Liu et al., 2023) recommendation (Wang et al., 2023c; Zhang et al., 2023), the world war (Hua et al., 2023) and communication game (Xu et al., 2023) have been explored to provide insights on communication. Most works only require a small number of agents and haven't considered scenarios requiring large-scale agents.

6.2 Social Simulation

Previous agent-based models for social simulation on opinion dynamics mainly focus on how individuals change their attitudes due to others' influence (Chuang and Rogers, 2023). These models can be divided into deductive ABMs and inductive ABMs. Represented by the Bounded Confidence Model (Deffuant et al., 2000), the former category is based on the psychology of attitude, such as the social judgment theory (Sherif and Hovland, 1961). By contrast, the latter often involves human experiments, which are expensive and with limited scale. With ability in human-level intelligence, LLM-empowered agents have potential to serve as a substitute for human subjects. Park et al. and Törnberg et al. provide a simulation platform to help designers see beyond social interactions that people intend and improve social interaction. Sotopia (Zhou et al., 2023) designs an evaluation framework for social intelligence. S^3 (Gao et al., 2023) simulate public opinion through Markov Chain and LLMs, but how they deal with the large scale of users remains ambiguous.

³https://developers.perspectiveapi.com/

7 Conclusion

In this paper, we propose a hybrid framework for social media user simulation. We empower core users and ordinary users with LLMs and ABMs, and we provide a Twitter-like environment and a benchmark SoMoSiMu-Bench for simulation and evaluation. Experiment results demonstrate the effectiveness and flexibility of our method.

Limitations

Our work is the first step towards a large-scale simulation implemented by a hybrid framework and it is limited in two aspects. In terms of data, although we have incorporated a larger number of agents than other studies, due to limitations in annotation costs, we have not yet validated interactions among millions of agents. In terms of LLM-empowered agents, due to reinforcement learning techniques, LLMs are also biased toward being more polite, articulate and respectful than users on real-world social media platforms (Törnberg et al., 2023), bringing bias to our study. More careful prompt engineering will be considered to solve this problem in future work.

Ethics Statement

Data Collection and Privacy Our data collection is in compliance with Twitter's terms of service and matches previous publications. Although tweets are public, when releasing data, we will share tweet id rather than raw data, to minimize the privacy risk. Furthermore, during the simulation, we anonymize each user by renaming them.

Simulation for Social Good The purpose of this paper is to use simulation to recreate the real situation of social movements and provide insights for improving harmonious communication among users. But it might also be misused to label people with a specific label that they do not want to be associated with. We suggest that when in use the tools should be accompanied by descriptions about their limitations and imperfect performance, as well as allow users to opt out from being the subjects of measurement.

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A Data Collection

A.1 Tweets of Social Movements

We get tweet ids of the three social movements from Maiorana et al., Chang et al. and (Giorgi et al., 2022), and crawl those during the required event periods. Overall, a total of 4,985,000, 22,869,406, and 25,112,678 tweets were collected. Subsequently, we sample users described in Sec 4.1 from the authors of these tweets.

A.2 Annotation

We annotate the stance and content type expressed in users' tweets and simulated content using GPT-3.5-turbo API, with the following prompt templates:

Prompt for Stance Annotation

What's the author's stance on {target}? Please choose from Support, Neutral, and Oppose. Only output your choice.

Text: {text}
Stance:

Prompt for Content Annotation

Please classify the text into one of the following categories based on its content. Only output your choice.

- 1. call for action: tweet contained a call for action (e.g. requesting, challenging, promoting, inviting, summoning someone to do something).
- 2. testimony: tweet contained a testimony of the victim (e.g. report, declaration, first-person experience).
- 3. sharing of opinion: e.g. retweets, evaluation, appreciation, addition, analysis of opinions.
- 4. reference to a third party: reporting on something/-one, direct and indirect quotes.
- 5. other: other content that does not fall into the above categories.

Text: {text}
Answer:

B Simulation Details

B.1 Parameters of ABMs

As mentioned in Sec 4.3, we find the best parameter combinations by parameter sweeping on the data of E1 or P1 for each movement. The parameter combinations used in pure ABMs and our hybrid models are illustrated in Table 5. The explanations of each parameter is as follows:

- alpha: the strength of the social influence of source agents;
- bc_bound: the confidence bound of the agents in the Bounded Confidence Models:
- init_uct: the uncertainty term in the Relative Agreement Model;
- acc_thred: the threshold for the latitude of acceptance of the agents in the Social Judgement Model;
- rej_thred: the threshold for the latitude of rejection of the agents in the Social Judgement Model;
- lambda: hyperparameter specifying the shape of the similarity bias function in the Lorenz Model;
- k: hyperparameter specifying the shape of the similarity bias function in the Lorenz Model;
- tho: the degree of assimilation, which controls the relative contribution of the assimilation force versus the reinforcement force in the Lorenz Model.

B.2 Simulation Settings

For all the experiments, we run the simulator on a Linux server with a single NVIDIA GeForce RTX 4090 24GB GPU and an Intel(R) Xeon(R) Gold 6226R CPU. The average cost for the whole simulation is around 20 dollars. For each event, we simulate 14 steps, with the step size estimated by comparing the peaks and valleys of simulated attitudes with that of the empirical data. We use one single OpenAI API key and a single simulation takes 5.7 hours on average.

Dataset	Models	alpha	bc_bound	init_uct	acc_thred	rej_thred	lambda	k	tho
	ВС	0.10	0.30	-	-	-	_	-	_
Metoo	HK	0.25	0.10	-	_	-	-	-	-
	RA	0.30	-	0.20	-	-	-	-	-
	SJ	0.15	-	-	0.10	0.90	-	-	-
	Lorenz	0.10	-	-	-	-	1.00	2.00	0.90
	BC	0.15	0.10	-	-	-	-	-	_
	HK	0.25	0.10	-	_	-	-	-	-
Roe	RA	0.10	-	0.20	-	-	-	-	-
	SJ	0.30	-	-	0.10	1.90	-	-	-
	Lorenz	0.10	-	-	-	-	2.00	10.00	0.50
	ВС	0.15	0.10	-	-	-	-	-	_
BLM	HK	0.10	0.10	-	-	-	-	-	-
	RA	0.10	-	0.20	-	-	-	-	-
	SJ	0.20	-	-	0.50	1.50	-	-	-
	Lorenz	0.10	-	-	-	-	2.00	2.00	0.30

Table 5: Calibrated parameters of the ABMs. "-" denotes non-applicable parameters.