Unlocking the Dynamics of Social Networks: Community-level Agent-based Social Simulation for Social Movement Evolution

Anonymous ACL submission

Abstract

The rise of online social media has significantly changed how people interact and form communities. It is important to understand how social movements evolve in this new era. However, current social simulation models, such as the Friedkin-Johnsen Model (FJ), Deffuant-Weisbuch Model (DW), and Hegselmann-Krause Model (HK), only consider the social network as a closed system without accounting for external events. The emergence of Large Language Models (LLMs) provides a new opportunity for social simulations. In our paper, we introduce a new agent-based social simulation system called CommuSoSim. We group people with different views into communities and provide them with community-level LLMs. When no external events occur, users' views evolve based on agent-based models. However, when new events occur, different communities react differently, causing users to update their views based on these reactions. With the strong language understanding and generation ability of LLM-empowered social community agents, CommuSoSim has the ability to efficiently integrate both internal and external influences. Our extensive results demonstrate the effectiveness of our approach. On average, our community clustering accuracy is 79.67%, and our predictions for user stance evolution outperform traditional agent-based models by 18.43% in Pearson correlation and 10.15% in stance prediction accuracy.

1 Introduction

In recent decades, online social media has experienced tremendous growth in users, dramatically altering the dynamics of social movements. When an event occurs, individuals with differing perspectives tend to react in diverse ways, as depicted in Figure 1. These varied responses to real-life events can result in further impact and the advancement of social movements. While most social movements are peaceful, some may escalate in more extreme directions, particularly when fueled by information campaigns. Therefore, it is crucial to anticipate the evolution of social movements, as this can empower individuals through heightened awareness of online influence patterns. The primary approach to social simulation is through agent-based models (ABMs), in which the behavior of each agent is updated according to social rules (Friedkin and Johnsen, 1990; Deffuant et al., 2000; Rainer and Krause, 2002). However, these methods treat the social environment as a closed system and do not account for real-life events. As a result, they may fail to accurately predict changes in public opinion caused by new external events.

The recent advancements in Large Language Models (LLMs) have shown their capability in understanding and generating language (Brown et al., 2020), opening up new possibilities in agent-based simulations (Xi et al., 2023) and human-level intelligence (Wang et al., 2024). However, research on agent-based social simulation in large-scale online social networks is limited and faces specific challenges: (1) How to efficiently simulate users given the impracticality of assigning a LLM-based agent to each user? (2) How to accurately predict opinion changes of users over time with continuous new events?

To address these challenges, we propose a community-level agent-based social simulation system, where each agent represents a social community consisting of users with similar opinion patterns. Studies have shown that individuals with similar opinions can amplify each other's reactions to external stimuli (Acemoglu and Ozdaglar, 2011). Therefore, in our system, users in the same community will have similar reactions to external events. We have designed the CommuSoSim with four modules: (1) community detection module to cluster users into different communities based on historical opinions; (2) deductible agent-based simulator module to update users' opinions period-

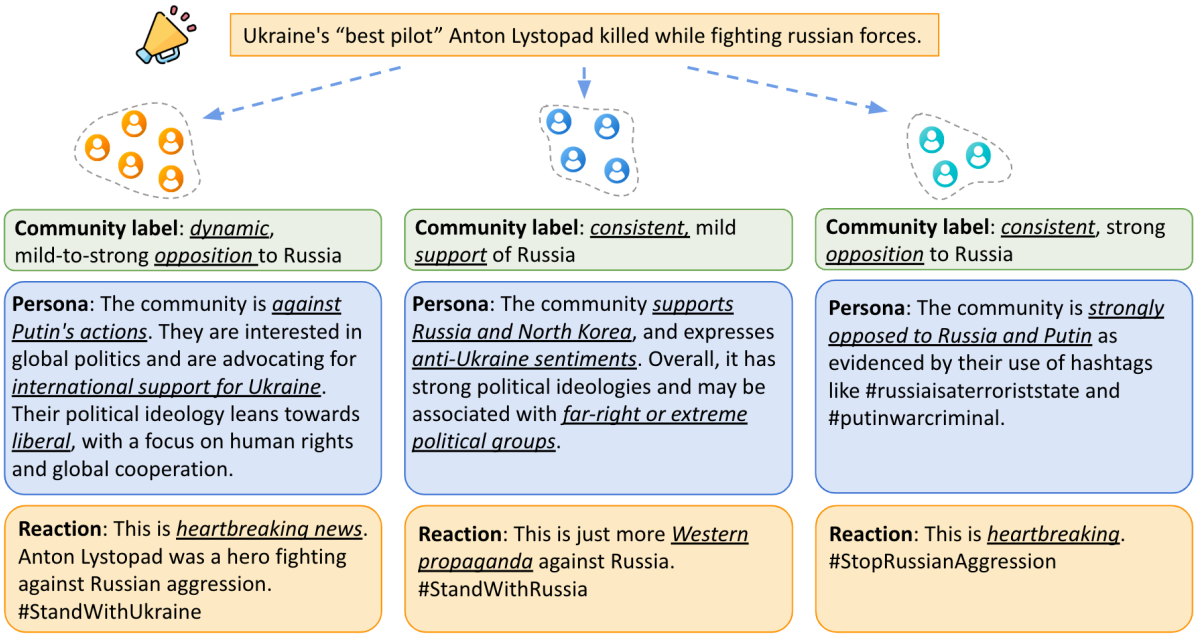

Figure 1: It's important to note that online users may have varying reactions and opinions about the same news. This pertains to the #StandWithRussia hashtag in the context of the Russia-Ukraine Conflict. The central assertion is based on actual events, and the subsequent content will outline the different responses from three distinct communities.

ically; (3) LLM-based community simulator module to construct LLM-empowered agents to generate community profiles and simulate their potential reactions to external news; (4) user stance update module, which considers both the network influence (simulated with deductible ABMs) and the news influence (simulated with community-level LLM-empowered agents). The overall framework is illustrated in Figure 2. Our key contributions include:

- We have developed a social simulator called CommuSoSim, which is powered by LLM (Large Language Model). This simulator takes into account the impact of real-life events in social simulations, making the social environment dynamic by incorporating external stimuli. This allows for more accurate capture of opinion changes.

- We designed community-level agents that can simulate users' reactions to real-life events based on the community persona. This not only improves the interpretability of the system but also makes effective use of LLM-based agents.

2 Related Work

2.1 Agent-based Social Simulation

The previous Agent-based Models (ABMs) for social simulation treated the social system as a closed system. They used theoretical frameworks and predefined rules to simulate and analyze complex social behaviors and interactions among agents within a virtual environment (Chuang and Rogers, 2023). The Friedkin-Johnsen (FJ) Model (Friedkin and Johnsen, 1990) suggests updating a user's stance with the weighted average of their neighbors' opinions and their own initial inherent opinion. The Deffuant-Weisbuch Model (DW) (Deffuant et al., 2000) simulates opinion updates through pairwise interactions, where people will adjust their views if their opinions are within a certain confidence threshold of each other. The Hegselmann-Krause Model (HK) (Rainer and Krause, 2002) updates agents iteratively by averaging the opinions of those users within a certain confidence interval. However, these approaches do not consider external stimuli, which are key factors in opinion variation. Our work proposes CommuSoSim, a LLM-empowered social simulation system that considers both the interactions among people and the influence of external stimuli (i.e., current affairs) to more accurately simulate the complex social media

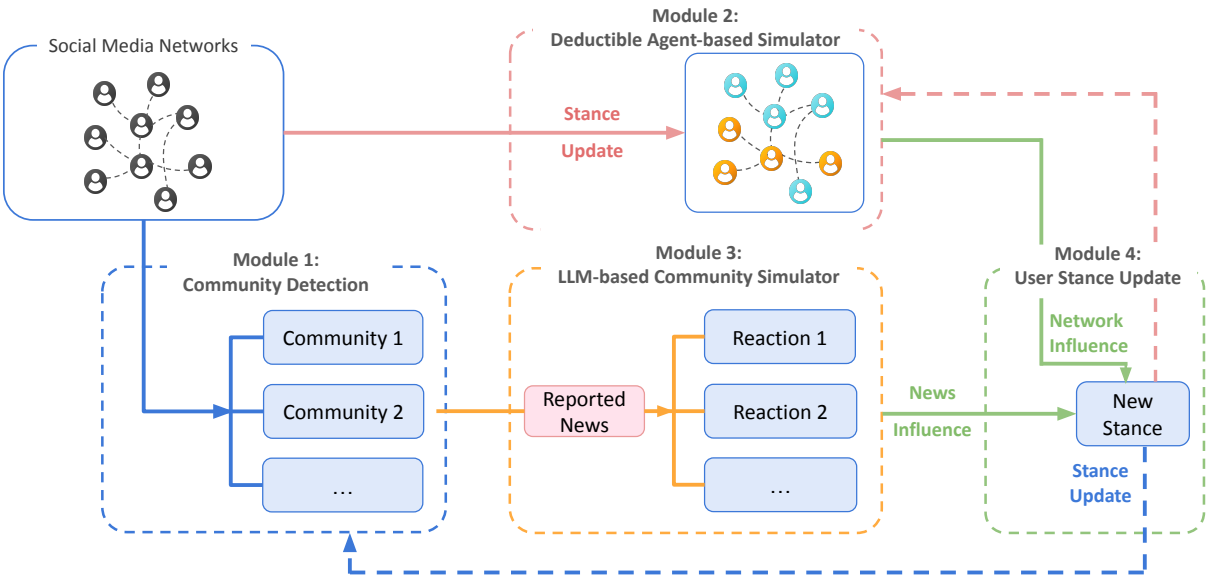

Figure 2: The process of updating stances in CommuSoSim is influenced by the social network structure and the community's response to real-life events.

environment.

2.2 LLM-empowered Agents for Social Simulation

The use of LLMs has led to an increase in research on LLM-empowered agents, which integrate profile, memory, planning, and action modules to create a virtual social environment (Wang et al., 2024). Liu et al. (2023) utilizes agent-based simulators for decision-making to enhance community regulations (Liu et al., 2023). Park et al. (2023) and Lin et al. (2023) establish a virtual town environment and create multiple agents to simulate human daily life (Park et al., 2023; Lin et al., 2023). Kovavc et al. (2023) investigates the social cognitive skills during child development using LLM-empowered agents' simulation (Kovač et al., 2023). Gao et al. (2023) simulates the propagation of information, emotion, and attitude in social networks (Gao et al., 2023). Jinxin et al. (2023) constructs a multi-agent simulation environment that maintains an agent's personality through a tree structure and simulates the environment of a classroom for cognitive simulation (Jinxin et al., 2023). Mou et al. (2024) designed LLM-based agents for influencers in the online social networks scenario to simulate the social movement (Mou et al., 2024). Our work focuses on large-scale social network simulation by constructing LLM-empowered agents to simulate community behavior, reducing the use of LLM-empowered agents while maintaining high quality user behavior simulation.

3 Problem Definition

Consider a set of n users $\mathcal{U} = \{u_1, u_2, ..., u_n\}$, each of whom have participated in online discussion around topic T by publishing or posting one or more assertions from a set of m assertions $\mathcal{A} = \{a_1, a_2, ..., a_m\}$, where each assertion has its stance. And a set of external future news $\mathcal{N}$ around topic T. Let $s_{u_i,t}, -5 \leq s_{u_i,t} \leq 5$ denote the stance of user a_{u_i} at time t. The sign of the stance represents the stance direction and the magnitude represents the extremeness of opinion, the larger the magnitude, the more extreme the assertion. The goal of CommuSoSim is to predict the future stance timeseries $S_{u_i} = \{s_{u_i,1}, s_{u_i,2}, ..., s_{u_i,t}\}$ of each user $u_i \in \mathcal{U}$ regarding topic T, t represents the time window user u_i posted an assertion.

4 Framework of CommuSoSim

The framework of CommuSoSim consists four modules: (1) community detection module, (2) deductible agent-based simulator module, (3) LLM-based community simulator module, (4) user stance update module. The process of CommuSoSim is shown in Figure 3.

4.1 community detection

Given the set of users $\mathcal{U} = u_1, u_2, ..., u_n$ and their previously posted assertion set $\mathcal{A} = a_1, a_2, ..., a_m$ regarding topic T, we apply GPT-3.5 to label the

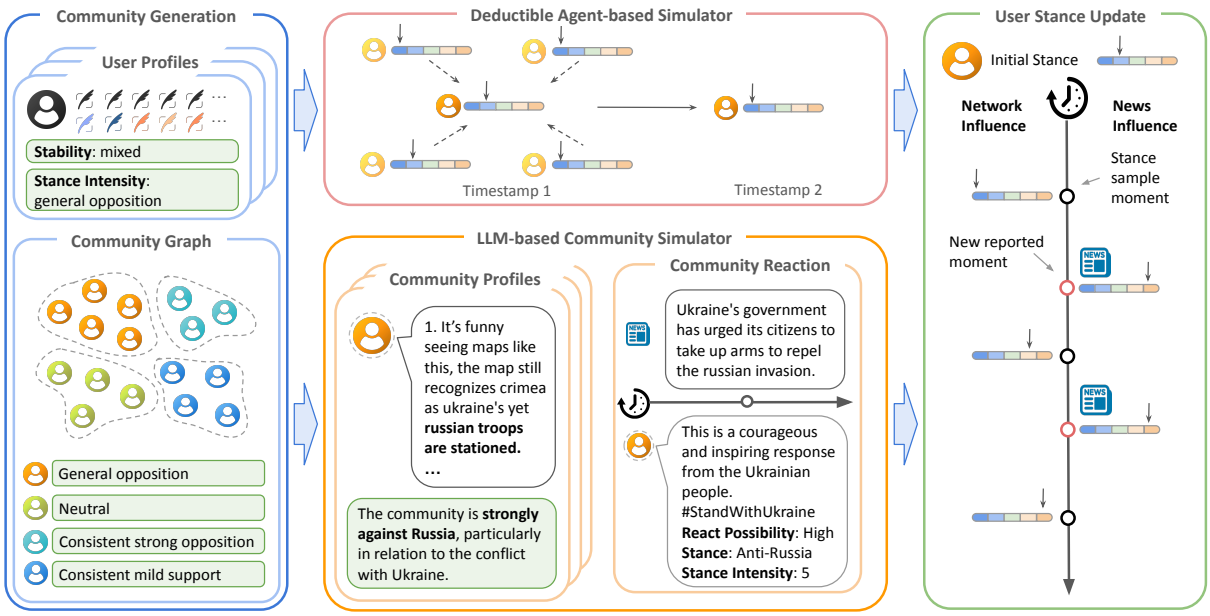

Figure 3: The CommuSoSim process comprises four main modules. The left part includes the community detection module, which groups users based on their historical posts related to the topic. The upper middle part contains the deductive agent-based simulator module, where users' opinions are updated using micro-level mathematical agent-based models. The bottom middle part houses the LLM-based community simulator, where LLM-empowered agents integrate the community's persona and simulate reactions to external events. The right part is the user stance update module, which considers both network influence and news influence.

stance of each assertion and form the history opinion dynamic timeseries for each user. Then we assign users to different communities based on their history opinion dynamics pattern. Figure 4 shows an example of assigning a user to the corresponding community. Examples of community labeling criteria are shown in Figure 5. The detailed community assignment criteria is shown in the Appendix A.

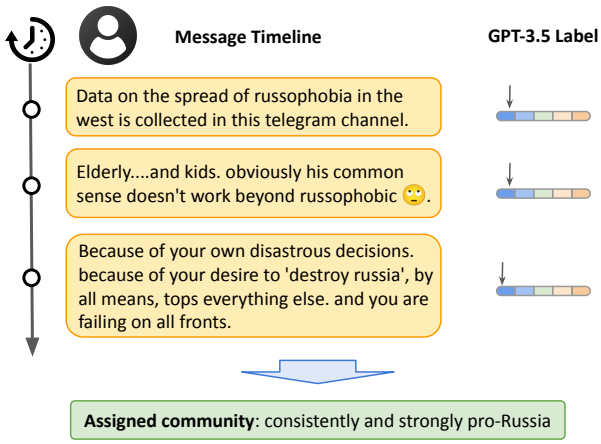

Figure 4: An example of assigning a user to the corresponding community.

4.2 Deductible Agent-based Simulator

We use the deductive agent-based model to simulate how users periodically update their opinions in the absence of external events. According to the survey by Chuang et al. (2023) (Chuang and Rogers, 2023), the process for deductive ABMs can be standardized into three parts: attitude update, neighbor selection, and message passing. The detailed procedure will be presented below.

4.2.1 Attitude update.

The attitude update module defines the attitude change from the current time window to the next time window. Formally, the attitude update can be represented as:

$$M_{u_i,t} = \{m_{u_j,t} | u_j \in N(u_i, t)\}$$
$$\Delta s_{u_i,t} = s_{u_i,t+1} - s_{u_i,t} = f_{update}(s_{u_i,t}, M_{u_i,t}), \quad (1)$$

where $\Delta s_{u_i,t}$ represents the attitude change of user u_i from time window t to time window $t+1$, $N(u_i, t)$ represents all neighbors of u_i, $M_{u_i,t}$ represents the messages user u_i receives from $N(u_i, t)$ at time t.

Definitions

support ratio: ratio of support opinion among the timeseries
oppose ratio: ratio of opposite opinion among the timeseries
mild support ratio: ratio of mild support (0 < opinion score < 4) among the timeseries
strong support ratio: ratio of strong support (opinion score > 4) among the timeseries
mild oppose ratio: ratio of mild oppose (0 > opinion score > -4) among the timeseries
strong oppose ratio: ratio of strong oppose (opinion score <= -4) among the timeseries

Communities

consistent mild support: support ratio greater than 0.5, oppose ratio is 0, strong support ratio is 0, mild support is greater than 0
consistent strong support: support ratio greater than 0.5, oppose ratio is 0, strong support ratio is greater than 0, mild support is 0
consistent mild oppose: oppose ratio greater than 0.5, support ratio is 0, strong oppose ratio is 0, mild oppose is greater than 0
consistent strong oppose: oppose ratio greater than 0.5, support ratio is 0, strong oppose ratio is greater than 0, mild oppose is 0
neutral: the larger value of support ratio and oppose ratio is smaller than 0.5

Figure 5: Examples of user communities labeling criteria.

4.2.2 Neighbour selection.

The neighbour module determines the neighbor set $N_{u_i,t}$ of user u_i at time window t. The neighbour selection can be driven by real-life social interaction networks, e.g. common hashtags (Pilař et al., 2021), common retweet (Yang et al., 2010), user follower/following patterns (Grabowicz et al., 2012), etc. In our paper, we define neighbors $N_{u_i,t}$ of u_i as the users who had common retweets with u_i based on history posts information and with the opinion score within a threshold compared with user u_i. Formally, the selected neighbors of u_i can be represented as:

$$N_{u_i,t} = f_{neighbour}(s_{u_i,t-1}, S_{t-1}), \qquad (2)$$

where $S_{t-1} = \{s_{u_j,t-1} | u_j \in \mathcal{U}\}$ represents the stance of all users at time $t-1$.

4.2.3 Message function.

The message function determines $m_{u_j,t}$ that would be transmitted to u_i based on the stance s_{u_j} of u_j. Formally, the message function can be represented as:

$$m_{u_j,t} = f_{message}(s_{u_j,t}) \qquad (3)$$

In our paper, we conduct $f_{message}$ following different function implementations, including Friedkin-Johnsen Model (FJ) (Friedkin and Johnsen, 1990), Deffuant-Weisbuch Model (DW) (Deffuant et al., 2000), abd Hegselmann-Krause Model (HK) (Rainer and Krause, 2002).

4.3 LLM-based Community Simulator

After creating user communities in Section 4.1, we develop LLM-empowered agents at the community level to enhance the system's responsiveness and efficiency in handling external events. The core model used is GPT-3.5. The LLM-based agent comprises a profile module, memory module, and action module, as illustrated in Figure 6.

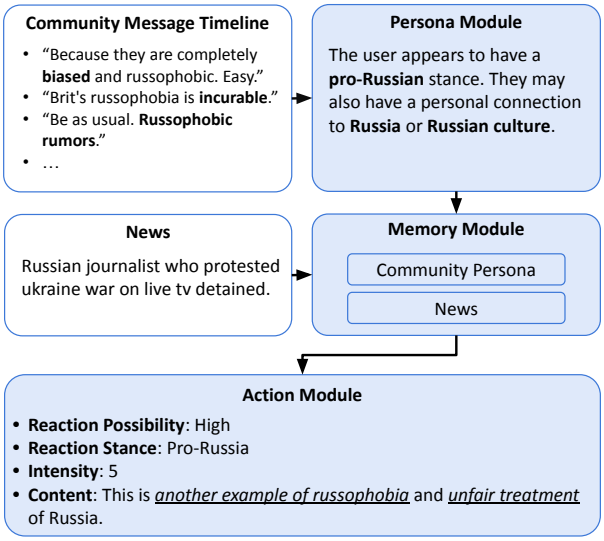

Figure 6: The LLM-empowered community-level agent consists of different modules. The left column contains input data, including historical posts in the community and external news. The upper middle part features the profile module, which contains descriptions of the community. The bottom part is the memory module, where the community persona and external news are stored. The right column houses the action module, where the agent generates actions based on potential responses, reaction possibilities, react stances, and intensity, all based on the community persona and news content.

4.3.1 Persona module.

The persona module takes the historical posts of all users in the community as input. The LLM-empowered community agent then generates the community persona based on aspects such as stance, psychographics, political ideologies, and the intensity of political ideologies leaning, all de-

rived from the history posts. The prompt for community persona generation is shown in Figure 7.

community persona generation

Summarize the persona of the community posting the following tweets in 3 sentences regarding the topic: *[topic]*. Include possible aspects such as **stance, psychographics, political ideologies, political ideologies leaning intensity.** The tweets are given below: *[tweets]*

Figure 7: The community persona generation prompt.

4.3.2 Momory module.

The memory module stores the community persona and external news. It writes the community persona as fixed profile information. Every time there's an external event, the memory module will store the incoming news information.

4.3.3 Action module.

The action module retrieves the community's persona and news from the memory module, and generates the community's reaction to external news. This includes the aspects of reaction possibility (high, medium, or low), reaction stance, reaction intensity, and reaction content. To simulate the community's reaction to news events, refer to Figure 8. If an event a occurs at time t, all users u_j in community c_i will be updated.

$$\Delta^{a}_{s_{u_j,t+1}} = w_a * s_{a,t}, u_j \in \mathcal{U}_{c_i}, \tag{4}$$

where w_a represents the update rate, which is converted from the react possibility $w_a^{high} = 0.8$, $w_a^{meduim} = 0.5$, $w_a^{low} = 0.2$. $s_{a,t}$ represents the stance of news a that happens at time t.

4.4 User Stance Update

The user's stance is updated considering both the network influence, which is simulated by the deductible agent-based simulator introduced in Session 4.2, and news influence, which is simulated by LLM-empowered community-level agent introduced in Session 4.3. The stance of u_i at time $t+1$ can be represented as:

$$s_{u_i,t+1} = \begin{cases} s_{u_i,t} + \Delta s_{u_i,t} + \Delta^{a}_{s_{u_i,t+1}}, & if\, a \text{ happens,} \\ s_{u_i,t} + \Delta s_{u_i,t}, & \text{otherwise.} \end{cases} \tag{5}$$

5 Experiment

5.1 Model and Dataset

The backbone LLM of CommuSoSim is GPT-3.5. We conducted experiments using three datasets obtained from Twitter[1]. The **Russia Slogans** dataset was collected using keywords such as "standwithRussia," "IstandwithRussia," or "IstandwithPutin." The **Russophobia** dataset was collected using keywords like "Russophobia," "Russophobic," "RussiaPhobia," or "Demonise Russia." The "EDCA" dataset was collected using keywords **EDCA** or "enhanced defense cooperation agreement." We filtered the dataset by selecting users who had posted at least two assertions in the test data and at least one assertion in the train data. For news data, we collected news from 19 different domains, including 'CNN,' 'nytimes,' and 'Reuters' for the **Russia Slogans** and **Russophobia** datasets. For the **EDCA** dataset, we collected news from domains such as 'cnnbrk,' 'CNN,' and 'cnnphilippines,' considering the close relation between this topic and the Philippines. Detailed statistics of the three datasets are shown in Table 1.

Table 1: Statistics of three Twitter datasets.

	Russia Slogans	Russophobia	EDCA
start time	2022-08-13	2022-08-04	2022-07-04
end time	2022-10-31	2022-08-25	2022-08-25
# user	274	2377	5204
# assertions (train)	1444	4119	4593
# assertions (test)	1560	4054	3840
# tweets (train)	3911	9316	5858
# tweets (test)	3094	8296	9154
# news	157	49	317

5.2 community detection

We use the training data to create community labels for each topic, following the criteria outlined in Appendix A. Then, we summarize the stance of the communities using the test data. The community labels and summaries are divided into two groups: **support** and **oppose**. We report the accuracy and F1 scores in Table 2. Additionally, you can find examples of community labels and stance summaries in Figure 9.

5.3 Stance Prediction

In the stance prediction section, we utilized the final opinion score from the training dataset for each user as the initial opinion score for every user. We employed GPT-3.5 to produce the ground-truth

[1] https://x.com/

community reaction simulation

A twitter community is with the persona described as *[persona]* regarding the theme *[topic]*. How would the user react to the news regarding *[topic]*: *[news]*? Answer the above question by filling in the <answer> below:
Potential response: <answer> (Respond in short.)
Possibility of making a reaction: <answer> (The possibility the community will share opinion or propagate this news. Select from low, medium, high.)
The stance of the user's reaction regarding *[topic]*: <answer>
The stance intensity of the user's potential reaction: <answer> (How intense it is of the author's stance? Choose from 0 to 5, with 5 be the most intense and 0 be the least intense. If the stance is Neutral, the intensity should be 0)

Figure 8: The community reaction simulation prompt.

Russia slogan
Community label: consistent strong **oppose**
Community persona: The community is **strongly against Russia** and anyone who supports or sympathizes with Russia in the Ukraine conflict. They have a very **negative and aggressive stance**, using derogatory language and making accusations. The community is likely to have a very intense **anti-Russia political ideology** and may lean towards extreme political ideologies or activism.

Community label: neutral - mild - strong **support**
Community persona: The user is **a strong supporter of Russia and President Putin**, taking a **pro-Russia stance** in the conflict. They express a **deep distrust of NATO and the West**, believing in the expansion of NATO towards Russia's borders. They also exhibit a strong **anti-Western sentiment** and a belief in **Russian superiority**, as well as a belief in conspiracy theories related to Ukraine.

Russophobia
Community label: consistent strong **support**
Community persona: The community appears to have a strong **pro-Russian stance**, as indicated by the use of the term "russophobic" and the defense of Russia in various tweets. They seem to lean towards **conservative political ideologies** and display a **high intensity** in their political ideologies.

Community label: mild - strong **oppose**
Community persona: The community is strongly **anti-Russian**, demonstrating russophobic tendencies and a **deep distrust of Russia and its government**. They also seem to have a strong stance against the Russian government's actions in Ukraine, leaning towards **pro-Ukrainian sentiments**. Their political ideologies lean towards anti-Russian nationalism and may have an intense dislike for Russian culture and influence.

EDCA
Community label: consistent mild **support**
Community persona: The community appears to be a strong supporter of the Marcos family and their political ideologies, showing a **pro-Western stance** and a **leaning towards a close alliance with the United States**. They are likely to have a conservative political ideology and a strong belief in maintaining strong military ties with the US.

Community label: consistent strong **oppose**
Community persona: The community is strongly **anti-Western**, particularly **against the presence and influence of the United States** in the Philippines, as evidenced by their criticism of the US-Philippines military drills and the Enhanced Defense Cooperation Agreement (EDCA). The user's political ideologies appear to lean towards a form of nationalism and **anti-imperialism**, with a focus on protecting Filipino sovereignty and interests.

Figure 9: Examples of community labels and community persona of three datasets.

Table 2: Consistency evaluation of community labels and content stance.

Topic name	Accuracy	Micro F1	Macro F1
Russia Slogans	0.8333	0.8333	0.8286
Russophobia	0.8462	0.8462	0.8375
EDCA	0.7857	0.7143	0.7083

stance label, and the prompt is displayed in Figure 10.

assertion labeling

Based on the tweet content below, describe the stance and stance intensity of the tweet by filling in the <answer> below.
Author's stance regarding *[topic]*: <answer> (Choose one from Pro-Russia, Anti-Russia, Neutral, Unrelated),
Author's stance intensity: <answer> (i.e., How intense it is of the author's stance? Choose from 0 to 5, with 5 be the most intense and 0 be the least intense. If the stance is Neutral, the intensity should be 0),
The tweet content is: *[text]*

Figure 10: The prompt of generating opinion scores for assertions.

5.3.1 Metrics.

We are comparing the accuracy of predicting a user's overall stance and the overall opinion dynamics trend of three topics. For the user's stance prediction, we report the accuracy. For overall opinion dynamics, we report the Pearson correlation (Sedgwick, 2012) between the real averaged opinion time series and the predicted averaged opinion time series. Additionally, we are estimating

Table 3: Statistics of three Twitter datasets.

Topic name	metrics	Pure FJ	CommuSoSim (FJ)	Pure DW	CommuSoSim (DW)	Pure HK	CommuSoSim HK
Russia Slogans	User Acc	0.6426	0.8441	0.5513	**0.8669**	0.5665	0.8137
	Pearson Corr	0.2270	0.3762	0.2848	**0.5095**	0.3042	0.5341
Russophobia	User Acc	0.5130	0.5274	0.5137	0.5370	0.6173	**0.6193**
	Pearson Corr	0.3854	0.4866	0.2315	0.4627	0.6183	**0.7066**
EDCA	User Acc	0.6840	0.7217	0.7055	**0.7307**	0.6732	0.7199
	Pearson Corr	0.5087	**0.6331**	0.4754	0.6049	0.5121	0.5922

Table 4: Costs of user-level LLM-empowered agent and community-level LLM-empowered agent among three Twitter datasets.

Topic name	User-level	Community-level
Russia slogan	53.27$	4.32$
Russophobia	202.31$	3.91$
EDCA	364.93$	3.73$

the potential cost of user-level LLM-based agent simulation system (by sampling users to construct agents and multiplying by the ratio) and the cost of community-level LLM-based agent simulation system.

5.3.2 Baselines.

In our comparison, we evaluated the performance of CommuSoSim by using Agent-Based Models (ABMs) to model all users and news, treating news domains as regular users. We conducted the experiment using the Friedkin-Johnsen Model (FJ) (Friedkin and Johnsen, 1990), the Deffuant-Weisbuch Model (DW) (Deffuant et al., 2000), and the Hegselmann-Krause Model (HK) (Rainer and Krause, 2002). For the FJ model, we set two layers of thresholds: 2 and 4. When the intensity difference between the user and its neighbor is within 2, the opinion update weight is 0.6. When the intensity difference is between 2 and 4, the opinion update weight is 0.4. For the DW model, the intensity difference threshold is 2, and the update weight is 0.6. For the HK model, the intensity difference threshold is 2.

Here are brief descriptions of the models:

- Friedkin-Johnsen Model (FJ) (Friedkin and Johnsen, 1990): This model describes how individuals' opinions evolve over time based on both their initial opinions and the influence of others within their social network.

- Deffuant-Weisbuch Model (DW) (Deffuant et al., 2000): This model simulates opinion dynamics by modeling how individuals with similar opinions adjust their views through pairwise interactions, leading to consensus or opinion clusters based on a confidence threshold.

- Hegselmann-Krause Model (HK) (Rainer and Krause, 2002): This model describes opinion dynamics where individuals update their opinions by averaging the opinions of all others within a certain confidence interval, leading to the formation of consensus or opinion clusters.

5.3.3 Result.

The results of user stance prediction accuracy and the averaged opinion timeseries are shown in Table 3, and simulation cost (and estimated simulation cost for the user-level simulation) is shown in Table 4.

As seen from the results, when considering news as external events and applying community-level LLM-empowered agents to make reactions, the simulators consistently outperform the pure ABMs in both metrics. This shows that the news has an important influence on public opinion. Additionally, the results uncover the effectiveness of using the community's reactions to external events to represent user reactions. The cost in Table 4 shows a significant improvement in cost when applying the community-level LLM-empowered agents instead of the user-level LLM-empowered agents.

6 Conclusion

In this paper, we introduce CommuSoSim, a social simulation system empowered by LLM (presumably a type of machine learning model) to simulate user communities in online social networks. Unlike traditional agent-based simulators, which treat the social network as a closed system, CommuSoSim considers external events, leading to more accurate prediction of opinion movement trends. Additionally, to maximize the effectiveness and efficiency of LLM-empowered agents, we use community reactions to represent user responses. Our results demonstrate the effectiveness and efficiency of this simulation framework.

7 Limitations

At present, we categorize the community based on users' tweet history, ideology, and stability. This approach may result in inaccurate simulations when there is insufficient historical user data. Additionally, the only external source currently utilized is news. In the future, we plan to incorporate more diverse real-life data, such as GDELT events, to enhance the range of external resources.

References

Daron Acemoglu and Asuman Ozdaglar. 2011. Opinion dynamics and learning in social networks. *Dynamic Games and Applications*, 1:3–49.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901.

Yun-Shiuan Chuang and Timothy T Rogers. 2023. Computational agent-based models in opinion dynamics: A survey on social simulations and empirical studies. *arXiv preprint arXiv:2306.03446*.

Guillaume Deffuant, David Neau, Frederic Amblard, and Gérard Weisbuch. 2000. Mixing beliefs among interacting agents. *Advances in Complex Systems*, 3(01n04):87–98.

Noah E. Friedkin and Eugene C. Johnsen. 1990. Social influence and opinions. *The Journal of Mathematical Sociology*, 15(3-4):193–206.

Chen Gao, Xiaochong Lan, Zhihong Lu, Jinzhu Mao, Jinghua Piao, Huandong Wang, Depeng Jin, and Yong Li. 2023. S^3: Social-network simulation system with large language model-empowered agents. *arXiv preprint arXiv:2307.14984*.

Przemyslaw A Grabowicz, José J Ramasco, Esteban Moro, Josep M Pujol, and Victor M Eguiluz. 2012. Social features of online networks: The strength of intermediary ties in online social media. *PloS one*, 7(1):e29358.

Shi Jinxin, Zhao Jiabao, Wang Yilei, Wu Xingjiao, Li Jiawen, and He Liang. 2023. Cgmi: Configurable general multi-agent interaction framework. *arXiv preprint arXiv:2308.12503*.

Grgur Kovač, Rémy Portelas, Peter Ford Dominey, and Pierre-Yves Oudeyer. 2023. The socialai school: Insights from developmental psychology towards artificial socio-cultural agents. *arXiv preprint arXiv:2307.07871*.

Jiaju Lin, Haoran Zhao, Aochi Zhang, Yiting Wu, Huqiuyue Ping, and Qin Chen. 2023. Agentsims: An open-source sandbox for large language model evaluation. *arXiv preprint arXiv:2308.04026*.

Hao Liu, Carmelo Sferrazza, and Pieter Abbeel. 2023. Chain of hindsight aligns language models with feedback. *arXiv preprint arXiv:2302.02676*.

Xinyi Mou, Zhongyu Wei, and Xuanjing Huang. 2024. Unveiling the truth and facilitating change: Towards agent-based large-scale social movement simulation. *arXiv preprint arXiv:2402.16333*.

Joon Sung Park, Joseph O'Brien, Carrie Jun Cai, Meredith Ringel Morris, Percy Liang, and Michael S Bernstein. 2023. Generative agents: Interactive simulacra of human behavior. In *Proceedings of the 36th annual acm symposium on user interface software and technology*, pages 1–22.

Ladislav Pilař, Lucie Kvasničková Stanislavská, Roman Kvasnička, Petr Bouda, and Jana Pitrová. 2021. Framework for social media analysis based on hashtag research. *Applied Sciences*, 11(8):3697.

Hegselmann Rainer and Ulrich Krause. 2002. Opinion dynamics and bounded confidence: models, analysis and simulation.

Philip Sedgwick. 2012. Pearson's correlation coefficient. *Bmj*, 345.

Lei Wang, Chen Ma, Xueyang Feng, Zeyu Zhang, Hao Yang, Jingsen Zhang, Zhiyuan Chen, Jiakai Tang, Xu Chen, Yankai Lin, et al. 2024. A survey on large language model based autonomous agents. *Frontiers of Computer Science*, 18(6):186345.

Zhiheng Xi, Wenxiang Chen, Xin Guo, Wei He, Yiwen Ding, Boyang Hong, Ming Zhang, Junzhe Wang, Senjie Jin, Enyu Zhou, et al. 2023. The rise and potential of large language model based agents: A survey. *arXiv preprint arXiv:2309.07864*.

Zi Yang, Jingyi Guo, Keke Cai, Jie Tang, Juanzi Li, Li Zhang, and Zhong Su. 2010. Understanding retweeting behaviors in social networks. In *Proceedings of the 19th ACM international conference on Information and knowledge management*, pages 1633–1636.

A Appendix

Figure 11 shows the community detection rules of communities based on users' history opinion scores.

Communities

consistent mild support: support ratio greater than 0.5, oppose ratio is 0, strong support ratio is 0, mild support is greater than 0
consistent strong support: support ratio greater than 0.5, oppose ratio is 0, strong support ratio is greater than 0, mild support is 0
mild - strong support: support ratio greater than 0.5, oppose ratio is 0, strong support ratio is greater than 0, mild support greater than 0
neutral - mild support: support ratio greater than 0 and smaller than 0.5, oppose ratio is 0, strong support ratio is 0, mild support greater than 0
neutral - strong support: support ratio greater than 0 and smaller than 0.5, oppose ratio is 0, strong support ratio greater than 0, mild support is 0
neutral - mild - strong support: support ratio greater than 0 and smaller than 0.5, oppose ratio is 0, strong support ratio greater than 0, mild support greater than 0

consistent mild oppose: oppose ratio greater than 0.5, support ratio is 0, strong oppose ratio is 0, mild oppose is greater than 0
consistent strong oppose: oppose ratio greater than 0.5, support ratio is 0, strong oppose ratio is greater than 0, mild oppose is 0
mild - strong oppose: oppose ratio greater than 0.5, support ratio is 0, strong oppose ratio is greater than 0, mild oppose greater than 0
neutral - mild oppose: oppose ratio greater than 0 and smaller than 0.5, support ratio is 0, strong oppose ratio is 0, mild oppose greater than 0
neutral - strong oppose: oppose ratio greater than 0 and smaller than 0.5, support ratio is 0, strong oppose ratio greater than 0, mild oppose is 0
neutral - mild - strong oppose: oppose ratio greater than 0 and smaller than 0.5, support ratio is 0, strong oppose ratio greater than 0, mild oppose greater than 0

dynamic mild support mild oppose: support ratio greater than 0, oppose ratio greater than 0, larger value of support ratio and oppose ratio greater than 0.5, strong support ratio is 0, mild support greater than 0, strong oppose ratio is 0, mild oppose greater than 0
dynamic strong support mild oppose: support ratio greater than 0, oppose ratio greater than 0, larger value of support ratio and oppose ratio greater than 0.5, strong support ratio greater than 0, strong oppose ratio is 0, mild oppose greater than 0
dynamic mild support - strong oppose: support ratio greater than 0, oppose ratio greater than 0, larger value of support ratio and oppose ratio greater than 0.5, strong support ratio is 0, mild support greater than 0, strong oppose ratio greater than 0
dynamic strong support strong oppose: support ratio greater than 0, oppose ratio greater than 0, larger value of support ratio and oppose ratio greater than 0.5, strong support ratio greater than 0, strong oppose ratio greater than 0

neutral: the larger value of support ratio and oppose ratio is smaller than 0.5

Figure 11: The label criteria of different communities based on opinions.