

CONTEXT

¹ Social media platforms have played a key role in the polarization of social, political, and democratic processes. Social uprisings in the Middle East, Asia, and Central and South America have led to sudden changes in the structure and nature of society during this past decade [Lyn15, Fou20, Cen21, GZ23, Wik, Kir17]. Polarization across the globe has paved the way to the divergence of political attitudes away from the center, towards ideological extremes, sometimes resulting in fractured institutions, erratic policy making, incipient political dialog, and the resurgence of old discredited regimes [Gar17, IS15, NB17, Lyn15, FH23, GC23]. Democracy, viewed as a system of power controlled by the people, has been made vulnerable by severe polarization as opposing sides are seen as adversaries that compete against an enemy needing to be vanquished. As a result, popular election campaigns –including presidential ones– have compromised the basic principles of democratic election in some countries [Bea18, SNC⁺23, SH23, BDD⁺23]. All these scenarios have a common factor: social media interaction as a medium for *opinion formation* fueling polarization.

Social learning and opinion dynamic models have been developed to understand the role of specific social factors on the acceptance/rejection of opinions, such as the ones communicated via social media (see, e.g., [GS17, AAK⁺23, HX23, DGM14]). They are often used to validate how certain assumptions on human behaviors can explain alternative scenarios, such as opinion consensus, polarization, and fragmentation. In their micro-level approach, users are considered as agents that can share opinions on a given topic. They update their opinion by interacting with a selected group of users that have some influence on them (e.g., influencers, their family and friends). These dynamics take place at discrete time steps at which (some) agents update their opinion. For instance, an opinion model can deterministically update the opinion of all agents in such a time-step, while another one can non-deterministically update the opinion of a single agent. The

¹Introduction take from [ORRV24]

ultimate goal is to understand how the opinions of the agents, as a social system, are shaped after a certain number of steps.

This project aims at building a distributed system to specify, simulate, and analyze social interaction systems with dynamic opinion models. We will define a polarization measure on it and study the evolution of the system according to some parameters.

PROJECT DESCRIPTION

Below we outline the structure and interactions within the system we are building, detailing the roles of different agents (or users) and their expected behaviors.

Users. Regular users of this system engage in discussions on various topics. For instance, a topic can be “are vaccines good?”. For each topic, the agents have an opinion on that particular topic that we will model as a real number in the interval $[0, 1]$. If agent A thinks that vaccines are not good, they will assign to this topic a value close to 0. Conversely, if agent A supports the efficacy of vaccines, they will assign a value close to 1. If A does not have a strong opinion about this topic, they will assign a value close to 0.5. We use $O_A(T)$ to denote the opinion of agent A on a topic T .

In order to be part of the system, the users need to log in a centralized server.

Influences and Interactions. An interaction occurs when a user A sends to another user B a message with their opinion on a given topic T , i.e., A sends to B the value $O_A(T)$. If this is the first interaction between A and B , B will define a *degree of influence* i_{AB} , that we model as a real number in the interval $(0, 1]$. A value close to 0 indicates minimal influence, while a value close to 1 indicates that A will have a strong influence on B . For this project, the initial opinion of an agent on a given topic ($O_x(T)$) and the degree of influence between agents (i_{xy}) will be randomly generated numbers.

When an interaction occurs between A and B , B ’s opinion on topic T updates according to the formula:

$$O'_B(T) = O_B(T) + (O_A(T) - O_B(T)) \times i_{AB}$$

where $O'_B(T)$ denotes the new opinion of B about the topic T .

Users must query the central server to obtain the IP address and port of the intended recipient for communication. The system operates in a fully distributed manner, with direct point-to-point communication between users. The server **does not** store opinions, degrees of influence, or discussed topics.

Some users are more active than others. The frequency of message sending is determined by random numbers.

Critical thinkers (CT).

CTs check the received information before updating their opinions since it might happen that the message received is a fake news. When a CT B receives a message from another user A , B requests evidence from A to “validate” their opinion. The evidence x ,

represented as a number randomly generated by A , must meet certain conditions for B (e.g., B accepts the evidence if x is a multiple of 7) to update their opinion. A cannot know whether B is a CT when interacting. Hence, A must always be prepared to provide evidence when requested.

Influencers. Influencers broadcast their opinions about a given topic to multiple users simultaneously. The users that receive such messages update their opinions as explained above. Since influencers are not willing to provide any evidence, a *critical thinker* B will never update their opinion when receiving a message from an influencer. Furthermore, influencers are resistant to change their opinions, and this is reflected in the *degree of influence* they assign to other users.

Proposers. These users introduce new topics for discussion. When a new topic is registered, the server must notify all the users that such a new topic is now discussed and agents can start communicating their opinions.

Consensus finders (CF). A CF searches for pairs of agents A and B in the network and “make them talk” to find a consensus about a given topic T . For that, the CF makes a “call” to A and B . If both of them accept (again, you can use random numbers to automatically simulate the fact that A and/or B answer the call), they will both change their opinion to the average $(O_A(T) + O_B(T))/2$.

Polarimeters. These agents measure the polarization of the system on a given topic T every t seconds. For that, they query the opinion of all the agents about T and compute the Esteban and Ray [ER94] polarization measure as follows: (1) They build an histogram, counting the number of agents whose opinion is in an given interval². Let’s call π_i the number of agents in a given interval i and m_i the midpoint of the interval i . (2) The polarimeters compute the following expression:

$$P = K \sum_{i \in I} \sum_{j \in I} \pi_i^{1+\alpha} \times \pi_j \times |m_i - m_j|$$

where $K > 0$ and $\alpha = 1.6$.

SOME EXTRA NON-FUNCTIONAL REQUIREMENTS

1. Avoid reading information from the keyboard and use random numbers when needed as explained above. Use parameters in your `main` classes to provide the values needed. For instance, for launching a *proposer*, one should execute:

```
java Proposer --topic="are vaccines good?" ...
```

Similarly, we can define the period t for the polarimeters as follows:

²You can discretize the interval $[0, 1]$ as $[0, 0.2)$, $[0.2, 0.4)$, $[0.4, 0.6)$, $[0.6, 0.8)$ and $[0.8, 1.0]$.

```
java Polarimeter --delay=5000
```

2. Use Java Logging ³ so that all the agents leave a log, informing the different events of the system: a message arrived, the opinion was updated, the evidence was not provided, etc.
3. Think very carefully how to synchronize the different threads of each class and the communication mechanism (TCP, UDP, RMI, etc) that fits better your needs. Ask yourself questions such as: Which methods need to be *synchronized*? What happens if the expected message does not arrive? What if someone is sending an opinion about a topic *T* that I'm not aware of? Should I compute a polarization measure even if some agents did not send their opinions on time?

DELIVERABLES AND RULES

The project must be developed in groups of 3 or 4 students (no exceptions). Only one student per team must submit on Moodle a Zip file containing:

1. The source code, fully documented using Javadoc. Write in the header of the file a precise description of the purpose of the class and your design choices. For instance, mention that “*this class uses the protocol X in order to communicate Y and the data structure D is protected using the synchronized method M, etc*”. You will loose **several points** if that information is not included.
2. A detailed README file explaining how to compile and use the system. Include in that file the commands needed to make the system work, for instance:

```
# Execute the server
java Server --port=1234

# Create some users
java User --conf1 --conf2 --conf3
java User --conf1' --conf2' --conf3'
java Influencer --conf1'' --conf2'' --conf3''
...

# Add some topics
java Proposer ....
...
```

3. The final score is **individual** and it heavily depends on the knowledge of the student about the code submitted and the answers to the technical questions asked during the day of the “exam”.

³<https://docs.oracle.com/en/java/javase/11/core/java-logging-overview.html>

4. Every student has to submit via Moodle an auto-evaluation form (see below).
5. It is strictly forbidden to communicate with other groups by any means. Fragments of code slightly similar will be considered fraud and severely punished.
6. If you are planning to use extra packages, besides those included in the Java standard library, you have to send an email to `olarte@lipn.univ-paris13.fr`. Non authorized packages will not be accepted as part of the solution.

There are two deliverables for this project:

1. On **19/04/2024**, one student per group has to submit a PDF including:
 - The name of the members of the team.
 - A Class Diagram (UML) for all the classes to be implemented.
 - A Sequence Diagram (UML) for each of the interactions the system must support. It is important to note that various small protocols need to be implemented in this project. Each of these protocols must be clearly described using a sequence diagram.
2. On **10/05/2024**, the zip file with the source code as explained above.
3. On **10/05/2024**, the auto-evaluation form.
4. On **13/05/2024**, we will have a session of questions for each group.

REFERÊNCIAS

- [AAK⁺23] Mário S. Alvim, Bernardo Amorim, Sophia Knight, Santiago Quintero, and Frank Valencia. A formal model for polarization under confirmation bias in social networks. *Log. Methods Comput. Sci.*, 19(1), 2023.
- [BDD⁺23] Andrew O. Ballard, Ryan DeTamble, Spencer Dorsey, Michael Heseltine, and Marcus Johnson. Dynamics of polarizing rhetoric in congressional tweets. *Legislative Studies Quarterly*, 48(1):105–144, 2023.
- [Bea18] Maren Beaufort. Digital media, political polarization and challenges to democracy. *Information, Communication & Society*, 21(7):915–920, 2018.
- [Cen21] Center for Strategic and International Studies. The #MilkTeaAlliance in Southeast Asia: Digital revolution and repression in Myanmar and Thailand. Visited 12-30-2023, April 2021.
- [DGM14] Abhimanyu Das, Sreenivas Gollapudi, and Kamesh Munagala. Modeling opinion dynamics in social networks. In *Proceedings of the 7th ACM International Conference on Web Search and Data Mining*, page 403–412, New York, NY, USA, 2014. Association for Computing Machinery.

- [ER94] Joan-Maria Esteban and Debraj Ray. On the measurement of polarization. *Econometrica*, 62(4):819–851, 1994.
- [FH23] Fitriani and Muhammad Habib. Social media and the fight for political influence in southeast asia. Visited 12-30-2023, August 2023.
- [Fou20] The Asia Foundation. *Violent Conflict, Tech Companies, and Social Media in Southeast Asia: Key Dynamics and Responses*. The Asia Foundation, San Francisco, USA, 2020.
- [Gar17] R. Kelly Garrett. The “echo chamber” distraction: Disinformation campaigns are the problem, not audience fragmentation. *Journal of Applied Research in Memory and Cognition*, 6, 2017.
- [GC23] Shelleka Gupta and Vinay Chauhan. Understanding the role of social networking sites in political marketing. *Jindal Journal of Business Research*, 12(1):58–72, 2023.
- [GS17] Benjamin Golub and Evan Sadler. Learning in social networks. Social Science Research Network (SSRN), 02 2017.
- [GZ23] Terri Gordon-Zolov. Chile’s estallido social and the art of protest. *Sociologica*, 17(1):41–55, January 2023.
- [HX23] Zhaoguo Xuan Haoxiang Xia, Huili Wang. Opinion dynamics: A multidisciplinary review and perspective on future research. *International Journal of Knowledge and Systems Science*, 2(4):72–91, 2023.
- [IS15] Torben Iversen and David Soskice. Information, inequality, and mass polarization: Ideology in advanced democracies. *Comparative Political Studies*, 48(13):1781–1813, 2015.
- [Kir17] E.J. Kirby. The city getting rich from fake news. BBC News Documentary, 05 2017.
- [Lyn15] Marc Lynch. After the arab spring: How the media trashed the transitions. *Journal of Democracy*, 26(4):90–99, 2015.
- [NB17] Kirill Neverov and Diana Budko. Social networks and public policy: Place for public dialogue? In *Proceedings of the International Conference IMS-2017*, page 189–194, New York, NY, USA, 2017. Association for Computing Machinery.
- [ORRV24] Carlos Olarte, Carlos Ramírez, Camilo Rocha, and Frank Valencia. Unified opinion dynamic modeling as concurrent set relations in rewriting logic. In *Proc. of Workshop on Rewriting Logic and Applications*, 2024.

- [SH23] Pratysush Sarma and Tanaya Hazarika. Social media and election campaigns: An analysis of the usage of twitter during the 2021 assam assembly elections. *International Journal of Social Science Research and Review*, 6(2):96–117, January 2023.
- [SNC⁺23] Vishnuprasad Padinjaredath Suresh, Gianluca Nogara, Felipe Cardoso, Stefano Cresci, Silvia Giordano, and Luca Luceri. Tracking fringe and coordinated activity on twitter leading up to the us capitol attack, 2023.
- [Wik] Wikipedia Foundation. 2021 Colombian protests. Visited 12-30-2023.