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Investigating Twitter Polarization and Information Flow with Agent-based Modeling

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Abstract

With social media being at the forefront of information diffusion, studying how it impacts the opinion dynamics amongst users is crucial to understanding and addressing the major negative impact that comes with polarization and echo chamber formation. This project utilizes the method of Agent-Based Modeling to simulate a Twitter network and user interaction. Followed by testing the model with varying parameters to conclude which of them has the highest impact on information diffusion. Experiments conducted on the model test the importance of endorsement, opinion flexibility, influence and public discussion on opinion dynamics. The results suggest that opinion diversity and connectivity are crucial factors that could avoid the emergence of echo chambers on polarized networks. Additionally, the project provides a user-friendly interface with graphical animations to visualize how information flows within an online community.

	Yes	No
I certify that all material in this dissertation which is not my own work has been identified.	☑	☐
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Introduction and Motivation

1.1 A new Era of Information Diffusion and Consumption

Preceding the rapid rise of information technology, by default, the primary method of acquiring knowledge and spreading information to a population was traditional media – this predominantly being: print, television and radio. The channels available for information diffusion were limited, therefore, a greater proportion of people got their information from a common set of sources. This meant that news outlets and broadcasters had a major role in shaping the political landscape and general public opinion [1]. However, with the rise of the 'digital age', spreading information has been faster, cheaper and easier than ever before; causing the main method of mass information diffusion to shift away from traditional media.

The accessibility of social networking and search engines has increased the convenience of person-to-person communication and made obtaining information more proficient. This technological takeover has pushed traditional media outlets to incorporate spreading information via digital means. Therefore, organisations such as large news outlets have had to adapt by incorporating websites and social media to retain their role in information regulation. Additionally, social media has also granted people the ability dynamically engage with and share information. It allows for a platform where individuals can contribute to online discussions and voice their opinions [2]. As a result, it provides a stage for people's opinions to be viewed, by an audience of people enabling them to potentially gain influence over a portion of public opinion.

Irrefutably, social media and digital communication had revolutionised information sharing. According to a survey conducted by the Pew Research Center found that approximately 86% of adults in the USA get news from digital means [3]. With platforms such as Facebook, Twitter and Reddit being dominant news sources for the public [4]. Therefore, these platforms are certainly hubs for information regulation in the news ecosystem. Social Networking enables users to access a great abundance of information that they can then choose to circulate within their own online network. However, the scope of gaining a vast range of information is disrupted by issues such as source credibility, the spread of misinformation and conspiracies [5], biases and filter bubbles. Additionally, with humans tending to associate themselves with others that share their beliefs, they risk not having exposure to a variety of perspectives which leads them to develop biases in their social and political opinions, especially on polarizing issues [6].

1.2 Polarization, Echo Chambers and the Consequences

Though there are many advantages to information diffusion on social media, there exist downsides that ultimately perpetuate polarization. These disadvantages cause the formation of closed communities, otherwise known as echo chambers – where individuals become isolated from opposing viewpoints [7]. On the one hand, it is the human characteristics, such as conformation bias and challenge avoidance, that enable echo chambers to emerge. On the other hand, it is the Social media companies: since these companies aim to expand and retain users, they employ feed customization algorithms that cater to what the user wants to see based on factors such as positive reinforcement. Due to this, information users see passes through a filter bubble, cementing individuals in their views as a result [8].

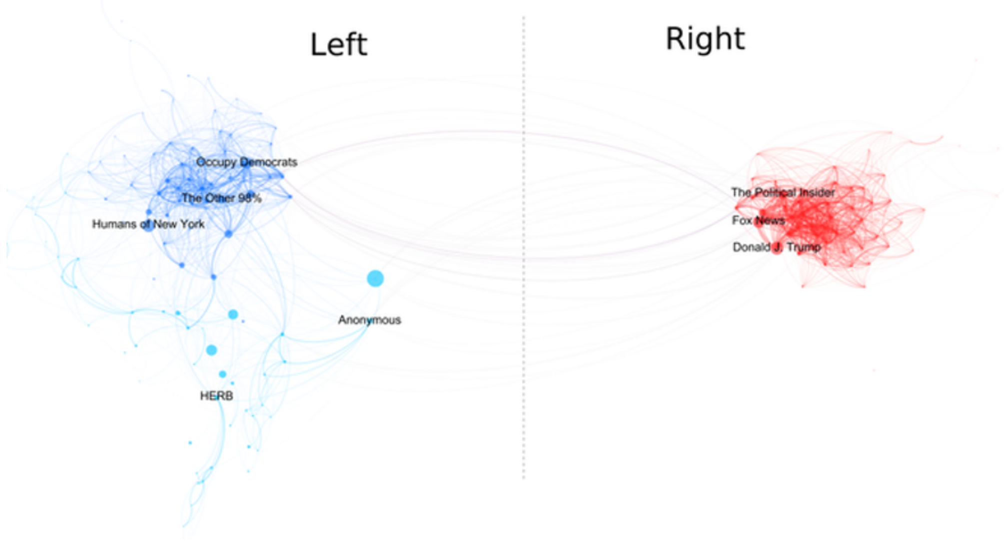

Figure 1.1: Visualization of lack of overlap between political left and right on Facebook [9]

Figure 1.1 demonstrates a study conducted on the presence of polarization-motivated echo chambers following the election of Donald Trump in 2016. The study found that users on opposite ends of the political scale share little to no common interests. [9]. The self-reinforcing cycle between polarization and echo chambers poses a threat to democratic decision-making and radicalization. In some cases, these closed communities contribute to real-world consequences. For instance, In the USA, during the 2016 election cycle, the conspiracy theory dubbed 'Pizza Gate' was a consequence of polarization amongst voters and false information spread within alt-right forums. The lack of critical opinions of the conspiracy led to a believer conducting a shooting at the pizzeria in question [10]. Another example related to misinformation spread within closed communities online is the anti-vaccine movement [11]. A study conducted on vaccine misinformation in the UK and USA found that the spread of false information resulted in an increase in vaccine hesitancy [12]. Within political referendums, Brexit was largely surrounded by social media discourse. A qualitative analysis conducted in 2017 found that Twitter was a hub for political debate and concluded it played a role in shaping public opinion [13]. When user activity was investigated, *Remain* supporters were found to exhibit interaction within echo chambers whereas *Leave* supporters engaged in cross-ideological interaction [14]. Evidently, information diffusion on social media materializes into real-world actions. Investigating the information flow on these platforms could present insights that help with understanding and addressing the issues that come with polarization and their effects within the political sphere.

2 Specification

2.1 Agent-Based Modeling

Investigating information dynamics as they actually exist on social media comes with challenges. Factors such as noise (i.e. bots, spam etc.) and issues concerning ethics and privacy, limit the scope of drawing conclusions from data. Additionally, observing a real network lacks control and flexibility, which makes it difficult to design experiments for studying this phenomenon. Agent-based simulations of these social media networks help overcome these challenges by allowing for realism along with the flexibility to observe information dynamics.

Agent-Based Modeling (ABM) is a tool utilized to simulate real-world scenarios. Therefore, it is an ideal way to observe specific factors affecting information flow such as polarization and influence. Creating an ABM consists of essentially two parts; The agent, which are given attributes and a set of well-defined rules. And the model – this sets up the environment where the agents exist. The model runs in time steps. At each time step, the agents carry out a set of actions and interactions that causes the model to change over time. Thus, observing how these interactions between these agents reflect on the model as a whole [15]. The study 'Modelling opinion dynamics in the age of algorithmic personalisation' highlights a successful applications of ABM in a similar context [16]. This method of modelling allows for monitoring and customizing specific parameters, which is necessary when seeking to identify factors affecting the public opinion landscape. Customisation of parameters, followed by running experiments to understand what factors influence change is an ideal way to study the effects of information flow and polarization within a network of users.

2.2 Scope

Twitter Simulation:
For this project, the agent-based simulation will be modelled after the mechanics of user interactions on the popular social media, Twitter. This is because Twitter's network structure and interaction dynamics make it ideal for creating a model that incorporates user interaction and influence. Finally, a series of experiments will be carried out to observe the effects of different factors causing polarization and the significance of user influence on opinions to test the competency of the model and report the findings.

Primary Aims:

- Build the model and calibrate it to replicate the aspects of user engagement on Twitter where agents are users that can carry out actions including posting, liking and retweeting. The model should allow for agent interactions to impact opinion dynamics and information flow.
- Design a series of experiments to run on the model facilitating the identification of the factors that impact polarization and user interactions.
- Produce graphs to compare and contrast the results to draw conclusions.

Secondary Aims:

- Create a graphical user interface that enhances the model's accessibility and user experience for better interaction with the different parameters.
- Incorporate an animation element for running the models. That also allows for observing the state of the network at each time step in an interactive way.

Limitations:
ABM's are reproductions trying to simulate real-world interactions and therefore, may omit some aspects of human communication online. For instance, this model does not account for the argumentative nature of online interaction between those from opposing sides. Additionally, as the size and complexity of the model grow, the computational demands become more significant, causing the model to run at a slower pace.

3 Project Development

3.1 Developing the Twitter Model

This model is developed in Python in combination with the framework and library Mesa and NetworkX. Mesa is a framework specialising in agent-based modelling with Python [17]. In this model, the network of users and their connections can be represented by a graph structure. Hence, the graphing library NetworkX is used to represent the agents and their environment. This library allows for convenient manipulation of node attributes which is essential when producing visualizations depicting the degree of polarization [18]. To initialize the starting network, custom graph builder functions are drafted using these NetworkX capabilities. Nodes in the graph have an opinion attribute that allows for initialising user agents and linking them to a node. Following the initialisation, a series of experiments can be conducted to test different parameters impacting the model. The specifics of these experiments are further discussed in section 3.2.

3.1.1 Agent-Based Model Breakdown

The Agents in this model represent the social media users. They are objects of the User class in this model. These agents have a set of defining attributes and actions that dictate their behaviour. Changing the value of some attributes invokes different outputs for a run of the model. The attributes are as follows:

- A unique ID number that identifies the user and associates them to a node on corresponding the graph.
- An opinion attribute, describes where the user lies on a polarization scale that ranges from -1 to 1 (0 being neutral).
- Every user has a list of their friends (or neighbours) - These are the users that a given agent has interactions with.
- A Timeline, this represents a user's screen holding the tweets published or retweeted by their neighbours. It is designed so duplicate tweets do not appear on the timeline. The timeline in

this model allows for up to 20 tweets to be housed at a time.

- A tweeting probability - This dictates the likely hood of a user publishing a tweet. It is represented by a number ranging from 1-100.
- Users have a list of their own tweets. This is to identify and track published tweets as it passes through the network.
- Opinion Flexibility - this is the likely hood of a user changing their opinion based on the information they consume. The flexibility is represented as a number ranging from 1 - 50. An opinion flexibility of 1 would indicate an opinion sway of 1:99 and 50 would be a 50:50 ratio between the user's own opinion and the average screen opinion. The lower a user's opinion flexibility, the less they are influenced by the information they read on their timelines.
- Users can also have an influence attribute. This attribute reflects how individuals or news organisations for example, with large followings, affect public opinion dynamics [19]. If a user has a high level of influence, the initial weight of the tweets they publish is increased. This attribute is set to zero by default and can be changed depending on the experiment conducted.

At each time step, the users complete a series of actions. The sequence of actions can be customized depending on what behaviour is being observed from the model. The actions are defined in methods. They are as follows:

- User agents can calculate their opinion flexibility depending on their degree of polarization. The function is designed in a way that the closer the opinion of a user is to the extremes, the less flexible they are to be accepting of views further from them. This method of calculating the opinion flexibility is a reflection of how further polarized individuals are less accepting of opposing views as shown in a study conducted on the role of news polarization on climate change [20].
- Users can create and publish tweets, this is the main method of interaction between users. A tweet exists as two parts: one part is what is sent to other users. It is represented as a list. This list contains a tweet ID, the user's own unique ID and the opinion at the time of making the tweet, and the users influence where applicable. The second part is for the author's list of published tweets. This is another list also containing the tweet ID, as well as a weight. The weight of a tweet is represented as an integer value that increments when a when the particular tweet is liked. Having the weight as part of the author's list of tweets ensures standardization for those viewing the tweet. Once a tweet is created, another method enables the tweet to be sent to their neighbour's timelines as long as their timeline is not full.
- Another function allows users to read their timeline, this is done at every time step. A user goes through each tweet, if the tweet opinion is within the endorsement index[1], they like

[1]The endorsement index is one of the parameters that can be tuned to observe opinion dynamics on the model. It is a decimal that determines the farthest opinion from their own a user will endorse.

and/or retweet it. The average timeline opinion is then calculated based on tweet weights. It then appends the user's own opinion with the following equation.

$$nO = \frac{(100 - f)O + tf}{100}$$

Where nO is the new opinion, O is the old opinion, t is the average timeline opinion and f is the opinion flexibility of the user. Additionally, depending on the chosen variables – while reading their timeline, if a tweet's opinion surpasses the drop threshold [2], the connection between the two users is severed if there is one.

- Users can also take part in opinion distancing. This method allows users to drop any of their connections based on their opinion. If they surpass the drop threshold regardless of them tweeting the connection dropped.
- Finally, users have the step functions that determines which of the actions stated above a user will do. For this project, the set of actions and corresponding parameters is divided into the experiments. Each experiment looks at the impact of a particular parameter. The experiments are discussed in further detail in subsection 3.2.

The Model sets up and monitors the environment of the simulation. It resides in the Network class of the program. This class tracks the overall behaviour of user interactions within the model. An instance of the Network takes in a graph and initializes the user agents based on the nodes of said graph. It also takes an experiment number, therefore, when user objects are initialized, the are done so with the according parameters to be tested and evaluated. This class houses the methods that allows user agent to modify the graph/node attributes. Apart from allowing modification of the network graph, the model tracks the change of general public opinion overtime, as well as the increase or decrease of polarization within the given network. The data accumulated within this class can then be plotted to observe the change in opinion dynamics.

3.2 Designing the Experiments

To test the competency of the model, A set of experiments were crafted to observe the different aspects of information diffusion. The first set of experiments attempts to investigate the level of impact 2 varied parameters, endorsement index and opinion-based distancing has on the degree of polarization within given networks. This set of experiments will be conducted on a graph with even distribution of connections and range of opinions.

- **Experiment 1: Investigate the impact of range of endorsement**. This experiment seeks out to identify what factors get users of opposing sides to interact with each other and at what level

[2]The drop threshold is a parameter that determines a users range of friendships. Depending on this, users are more or less likely to be friends with opposing view points

of willingness to like and retweet those with a different opinion do echo chambers emerge. This experiment will be carried out by varying the model's endorsement index. The range examined for this experiment has endorsement index at 1.5, 1, 0.5, 0.25, 0.125 and 0.05. These values are chosen as they cover the appropriate range of values to provide an understanding of the relationship between connectivity based on willingness to accept opposing bits of information. In this experiment users will only remove connections based on tweets on their timelines. The influence and opinion flexibility are constants to ensure they do not affect the results. To measure the impact of the different endorsement indexes, we can look at the number of connections that were dropped in within the network.

Hypothesis: A decrease in connectivity resulting in two polarized groups should be observed as the endorsement index decreases.

- **Experiment 2: Investigate the effect of opinion-based distancing**. With this experiment we can observe the impact of users dropping the connection with a neighbour as soon as their opinion falls outside the acceptance range. For this experiment, the drop threshold being tested are as follows: 1.5, 1, 0.75, 0.5, 0.25 and 0.05. Unlike experiment 1, the connectivity of the network is not determined my tweets on their timeline. Similarly, the influence and opinion flexibility also remain constant for these runs of the model.

  Hypothesis: Increase in polarization and echo chamber formation should be observed in the model as the likeliness accept users with further away opinions decreases.

The second set of experiments aim to observe the role of information regulation at the hand of users with high influence. This set also seeks to investigate what factors, such as public opinion and increased public conversation, can resist polarization. The following experiments are conducted with varying user dynamics.

- **Experiment 3: Investigating the impact of influence within a neutral community**. In this experiment, one node has it's influence attribute set to 100 and the opinion attribute set to the extreme on the scale from -1 to 1. The community are the rest of the nodes with mostly neutral opinions ranging from -0.3 to 0.3. This experiments shows us the effect of influence when no other factors act on opinion dynamics. The neutral community has an opinion flexibility that ranges between 1 to 50.

  Hypothesis: A neutral community with no other sources of information will be quick to converge to opinion of the influential user.

- **Experiment 4: Investigating the impact of influence within an opposing community**. This experiment seeks to observe the impact of high influence when met with push back at the hands of polarization. The node opinions within this community range form -1 to 0.

  Hypothesis: The increase in opposing opinions will slow down the rate of information diffusion originating from the influential node. The community will be less likely to endorse the opinions, however as the influencer node is the only source of tweet production in this experiment, will cause a slower shift compared to if the community was neutral.

- **Experiment 5: Investigating the impact of influence within a community with varied opinion flexibility**. This experiment seeks to observe the level of resistance to influential information from the opinion flexibility attribute. In a mixed opinion community. The node opinions within this community range form -1 to 1.

  Hypothesis: As users with opposing flexibility are less likely to change their opinion quickly the rate of information flow from the influencer node will be slower.

- **Experiment 6: Investigating Influence versus public communication**. This experiment seeks to see the effect of tweeting amongst users in combination with tweets originating from an influential node. The community for this experiment is the same as the one seen in Experiment 5. However, in this experiment, users other than the influential node can publish tweets.

  Hypothesis: The community in this experiment should show a significant resistance as the information circulation is of varied opinions.

3.3 Interacting with the Model: UI and Animations

For the visualization aspect of this project, the graphing library Plotly has been chosen to produce outcome graphs and animations. This library provides flexibility when designing visuals and tools to help customize animations. Additionally, it is seamless to use in conjunction with NetowrkX graphs allowing for clean animations to showcase the model changing over time [21].

Interaction with the model is achieved in two ways, the model can be run straight from the command line to run different experiments. Additionally, it can be interacted with via a web-based user interface (UI) created with the framework Flask. Flask was ideal for the application of the interface as it enables a locally hosted UI that could be easily set up by creating an HTML template and style sheet [22]. Incorporating a UI simplifies the process of modifying parameters and running the simulation. Additionally, it accommodates for running the model multiple times without needing to physically run the Python script from the command line.

3.3.1 Model Animation

Figure 3.1 depicts the evolution of a network as the model runs on an interconnected graph with polarized opinions. The series of images show the model animation at different frames in its progress. The interface features a control panel with buttons that allow the animations to be paused and played. This allows the animations to be stopped and studied at a given time step. The panel also has a slider element that allows for scrubbing back and forth to navigate through the different stages of the run. The colour-coded nodes correspond to an opinion depicted in the colour scale provided on the side. An Additional feature is observed in the visualizations when hovering a mouse over the node. It further provides information about particular nodes, such as opinion and number of connections.

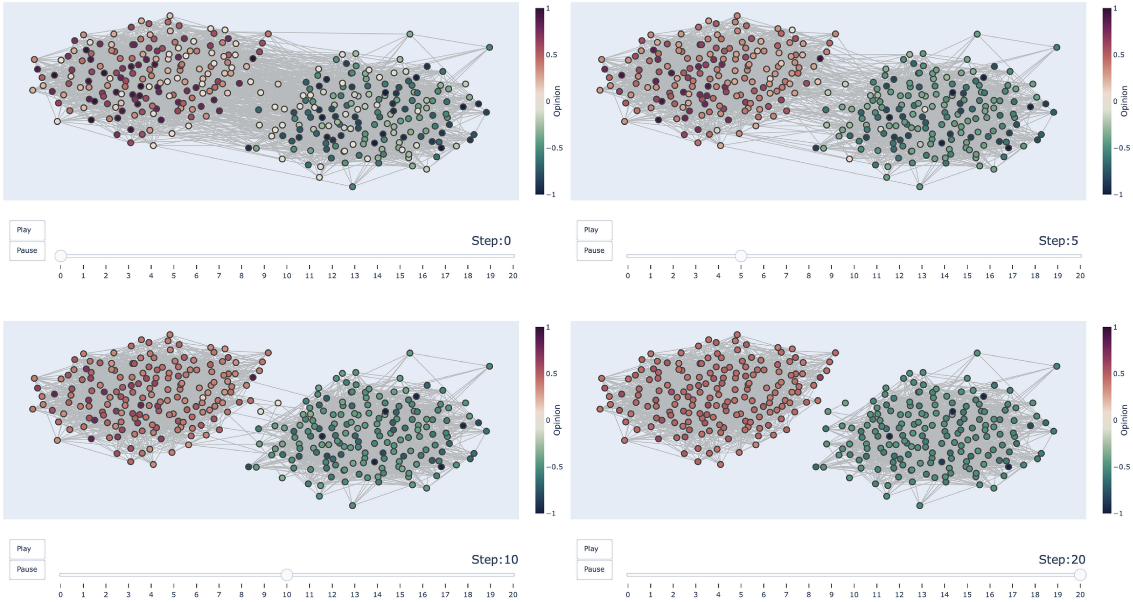

Figure 3.1: Model run demonstration for visualization capabilities

3.3.2 User Interface

Figure 3.2 showcases the interface. The UI is constructed to have a dashboard like structure. Each panel talks through the specifics of the different parameters that can be adjusted for the different experiments that can be run with the model. It accommodates input relating to an experiment and for the number of time steps for the the run. Once the 'Run Model' button is pressed, the model run is initiated. When completed, It navigates to the animated visualization of the run and produces graphs where appropriate, to view change over time plotted.

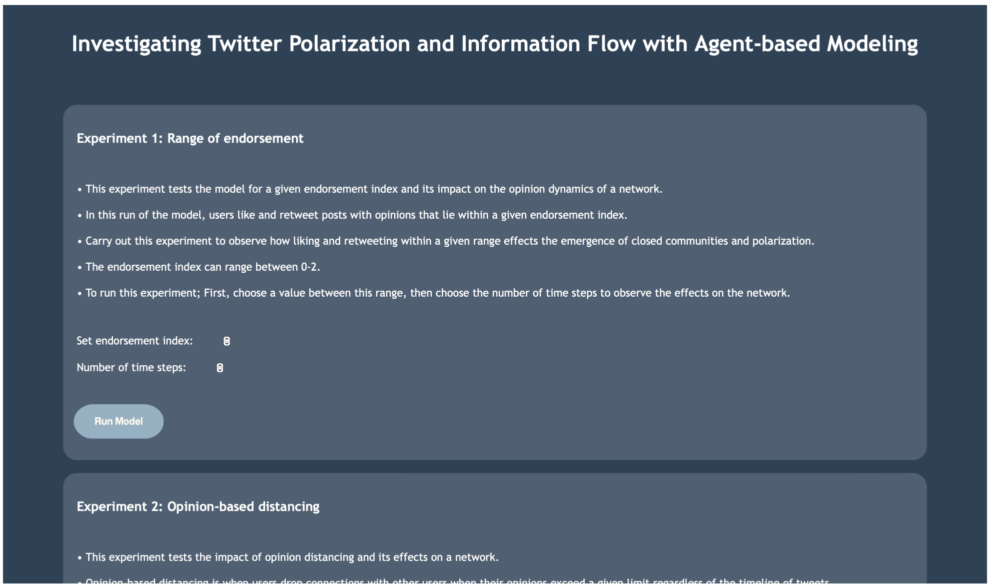

Figure 3.2: User Interface to interact with the model

4 Results

4.1 Which factors have the greatest impact on polarization and echo chamber formation?

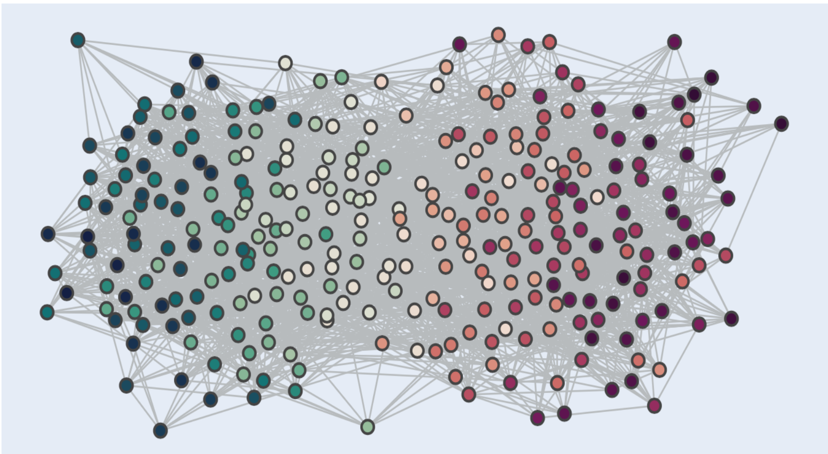

Figure 4.1: Visualization of network at step 0

The following two experiments were conducted on an even distribution network comprising of 300 users, with each experiment lasting 30 time steps. Figure 4.1 depicts the initial visual of the network before the run of the model. To ensure fairness, both experiments were conducted on the exact same graph to observe the behaviour of agent actions. The initial graph notably has a high degree of connectivity. There were 2746 edges and it had an initial beta index [1] of 9.15. Opinions ranged from the two extremes from -1 to 1. Overall, the objective of the following runs of the model aimed to shed light on the relative role of endorsement and opinion-based distancing and their impact on polarization and echo chamber formation on social media.

[1] In Graph Theory, the beta index describes the connectivity of a graph, calculated by edges over nodes.

4.1.1 Impact of Range of Endorsement

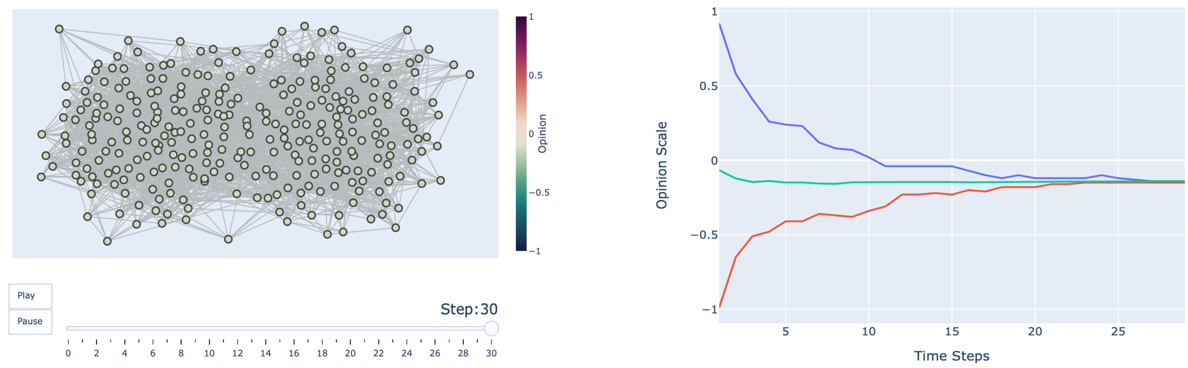

Figure 4.2: Endorsement Index 1.5

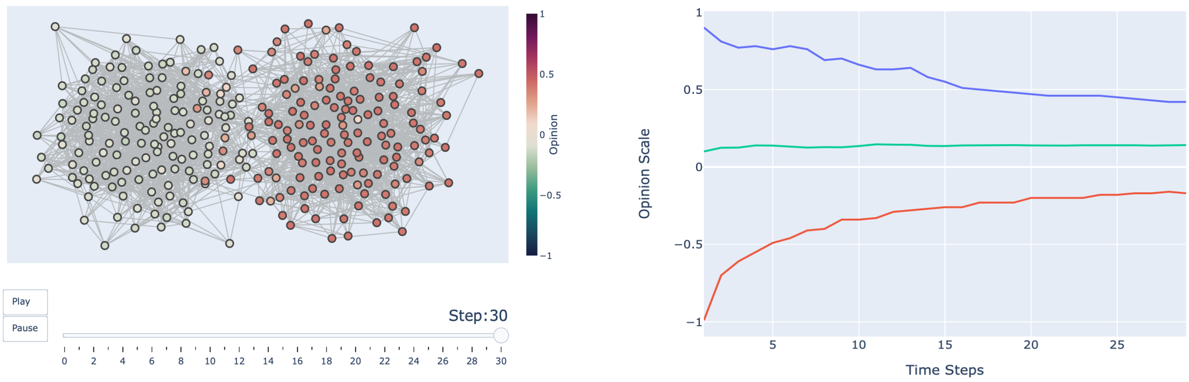

Figure 4.3: Endorsement Index 0.5

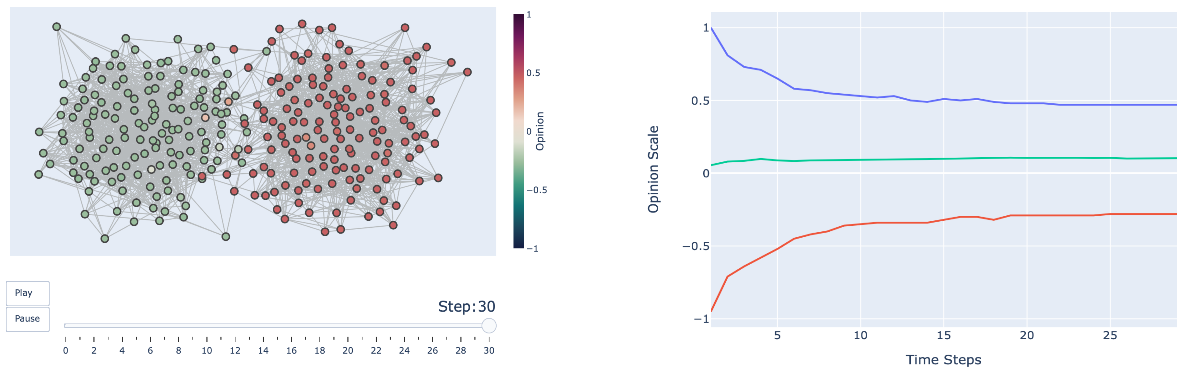

Figure 4.4: Endorsement Index 0.25

Evaluation:
The results of this experiment validate the hypothesis, the model behaviour is consistent and competent for experimenting on this parameter. The observed behaviour shows that as the endorsement index drops, so do the connections between user agents. Figure 4.2 depicts the final frame of the animation for an endorsement index of 1.5. It shows the eradication of polarization

when there is a higher level of endorsement. As there was higher connectivity, users were more likely to receive a varied range of perspectives leading to a lower level of polarization. The right image of Figure 4.2 shows the gradual convergence of the polarized groups. The green line on the graph represents the general public opinion and the red and blue represent the most polarized views in the model. It is observed that the endorsement index of 1 sees a drop in graph connectivity compared to 1.5. Regardless, the behaviour observed is similar to that for 1.5 and polarisation decreases. Figures 4.3 and 4.4 depict a decrease in connectivity based on an endorsement index of 0.5 and 0.25 respectively. Both visualizations show that the connectivity of the network has decreased, However when examined we see that users with an index of 0.5 show a lower degree of polarization than those at 0.25. An endorsement index of 0.125 has results nearly similar to an index of 0.25. Interestingly, it is observed that at an endorsement index of 0.05, the number of connections dropped is lower than at 0.125. This is because there was a quicker reduction in edges with nodes from opposing groups. This enabled the opinion within the 'potential' echo chamber to equalize before further connections were dropped. A summary of these results is presented in table 1 for further analysis and interpretation.

Table 1

Endorsement index	Connections Dropped	Steps to equilibrium	echo chamber observed
1.5	93	21	No
1	160	27	No
0.5	752	25	Yes
0.25	881	20	Yes
0.125	1144	20	Yes
0.05	1003	10	Yes

4.1.2 Effects of Opinion Distancing

Evaluation:
The results from the experiment testing dropping farthest neighbours are as expected. It shows the gradual drop of connections. However, the results of the first four parameters show an interesting pattern. Even though connections were dropped, it was insufficient in causing the emergence of echo chambers. The resulting visualization can be observed in Figure 4.5. This is because the degree of polarization decreases with a slower rate of connections being dropped. Further, it implies more connectivity leads to less polarization. It is between a drop threshold of 0.25 and 0.05 we observe polarization and echo chamber emergence, as seen in Figure 4.6. A drop threshold of 0.25 marks the level at which echo chambers start to emerge, at this level and below users are no longer complying with those with opposing opinions. The results can be seen summarized in the table 2 below.

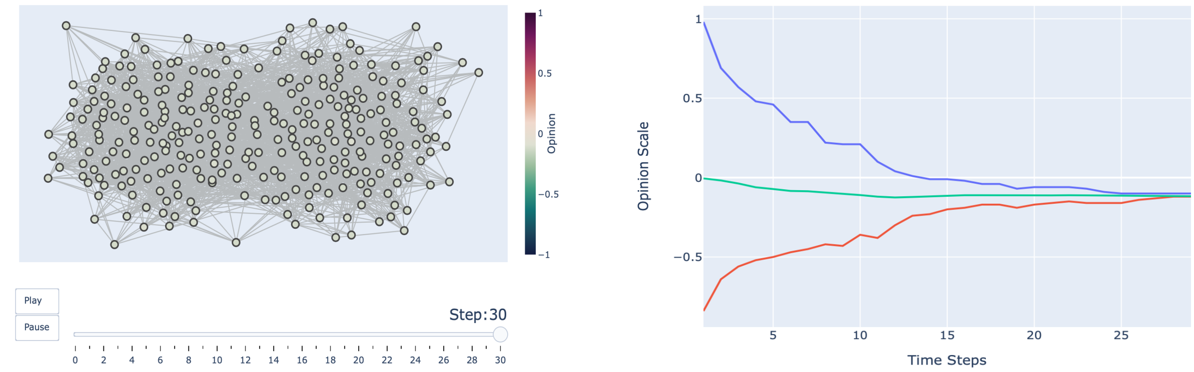

Figure 4.5: Drop Threshold of 1

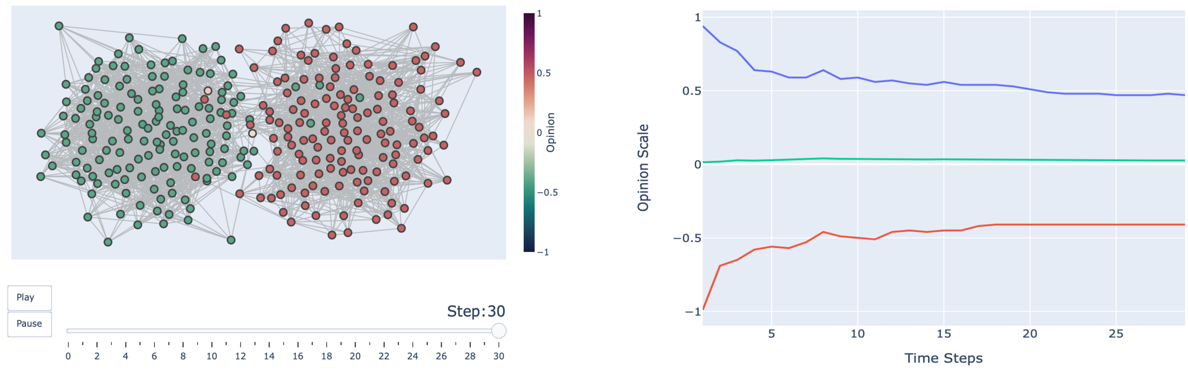

Figure 4.6: Drop Threshold of 0.25

Table 2

Drop Threshold	Connections Dropped	Steps to equilibrium	echo chamber observed
1.5	0	25	No
1	17	28	No
0.75	155	24	No
0.5	439	>30	No
0.25	666	20	Yes
0.05	747	18	Yes

4.2 What factors impact the authority of influence and public opinion

The following series of experiments explores the impact of high influence on a variety of types of communities as well as opinion flexibility and tweet probability. To ensure consistency, these experiments were conducted on a network of 300 users. However, unlike the first set of experiments, the model run is a 100 time steps as the changes were observed to occur at a slower rate when looking at influence rather than factors that observe connectivity. By testing influence against these varied parameters, it can be observed which of them has a more pronounced effect on the given community.

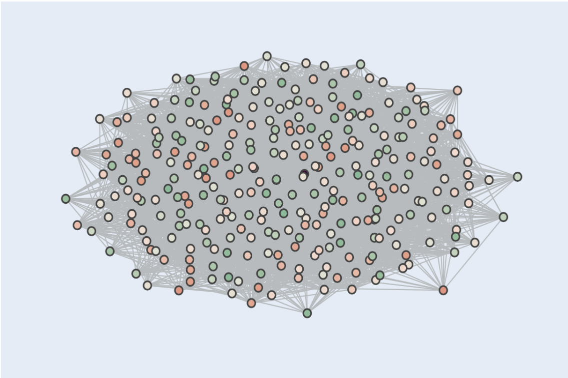

Figure 4.7

Figure 4.7 shows the initial neutral graph for examining the effects of influence. This experiment acted as a control to the subsequent experiments. As the high influence node was the only one propagating information diffusion within this graph the results of this run had the model at equilibrium within 20 time steps. With the neutral community being open to rethinking their opinions, and not possessing any other forms of rebuttal, all nodes converted to the opinion of the information they were fed within the first 20 time steps.

4.2.1 Influence on a Polarized Community

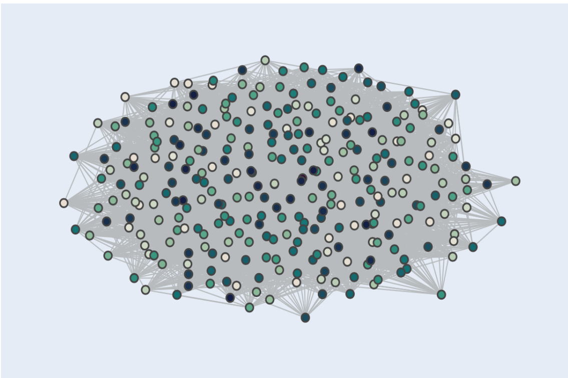

Figure 4.8

The experiment conducted on the network presented in Figure 4.8 revealed that the model reached a state of equilibrium in 60 time steps. The resulting network resembling a homogeneous cluster matching the opinion of the influential node. As hypothesised, the opposing community did not waver as quickly. Therefore, proving that distant opinions take longer to converge. Mimicking how a strongly polarized community is resistant to believing opposing perspectives. From this experiment, we can also conclude that as opinions get closer to influence, the rate at which they converge increases. This trend is likely attributed to the rate of retweeting increasing as public opinion moves closer to that of the influence.

4.2.2 Influence vs Opinion Flexibility and Influence vs Public Communication

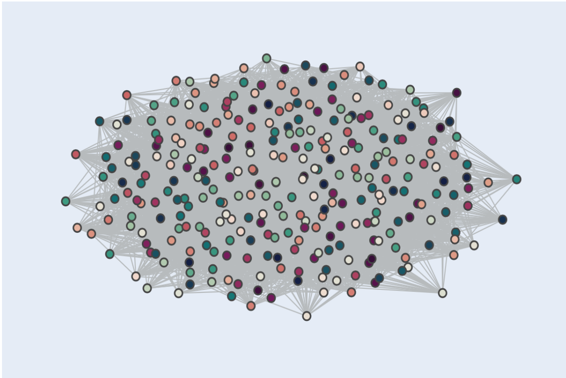

Figure 4.9

The final two experiments regarding the impact of influence were conducted on an even distribution graph, as seen in Figure 4.9. Experiment 6, examined the effects of opinion flexibility on the model. For this iteration, the results show that users with high opinion flexibility succumb to the influence, while those with a lower opinion flexibility, in combination with opinions at a farther distance from the influential user slow down the rate at which the model reaches equilibrium slightly. Finally, experiment 7 incorporates the characteristics of public discourse and discussion. Pointing to evidence that public discussion is a significant factor in dictating opinion dynamics.

4.2.3 Evaluation of Impact of Influence

The impact of influence on opinion dynamics has been studied through the four experiments explored above, and the results for each one against each other are presented in Figures 4.10 and 4.11. From these plots, it is observed that the neutral community is the most vulnerable to influence. It was the first to converge to the influence opinion. In second, it is experiment 3, showing the least impact to influence, indicating that opinion flexibility alone is not very effective in slowing down the rate of opinion change due to influence.

Figure 4.10 depicts the results of experiment 4. It shows that the resistance to influence when the number of users with a -1 opinion is larger. Resulting in a slower the rate of information diffusion as opposing users are not retweeting the influencer's tweets. However, it's evident that as the number of users at opinion -1 decreases and the quicker the opinions of the community converge with the influence depicted by the sudden incline observed in figure 4.10 at time step 20. Finally, there are the results of testing public communication. From the two graphs below, it is clear that this parameter has the most impact in combating the effects of influence. It highlights the importance and necessity of diverse opinions within all types of networks to prevent the formation of echo chambers. All things considered, it can be concluded that dynamic public reaction, communication and influence have the highest impact on the opinion dynamics of a given network.

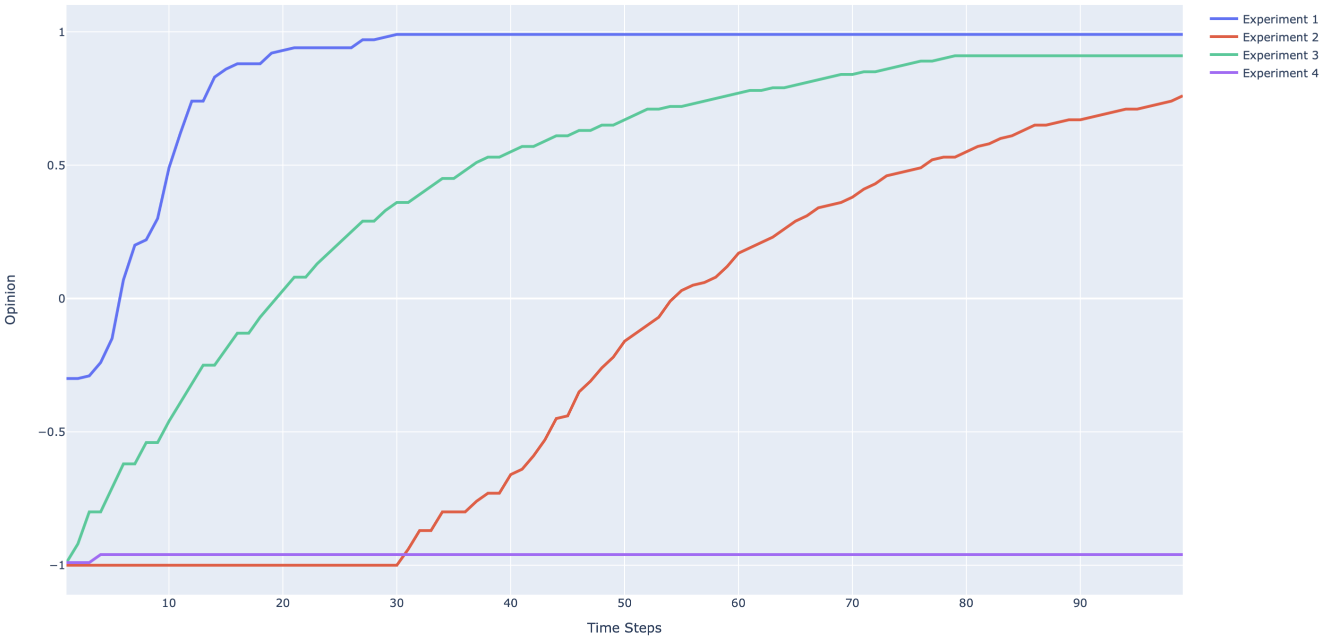

Figure 4.10: Role of influence: Impact on Polarization

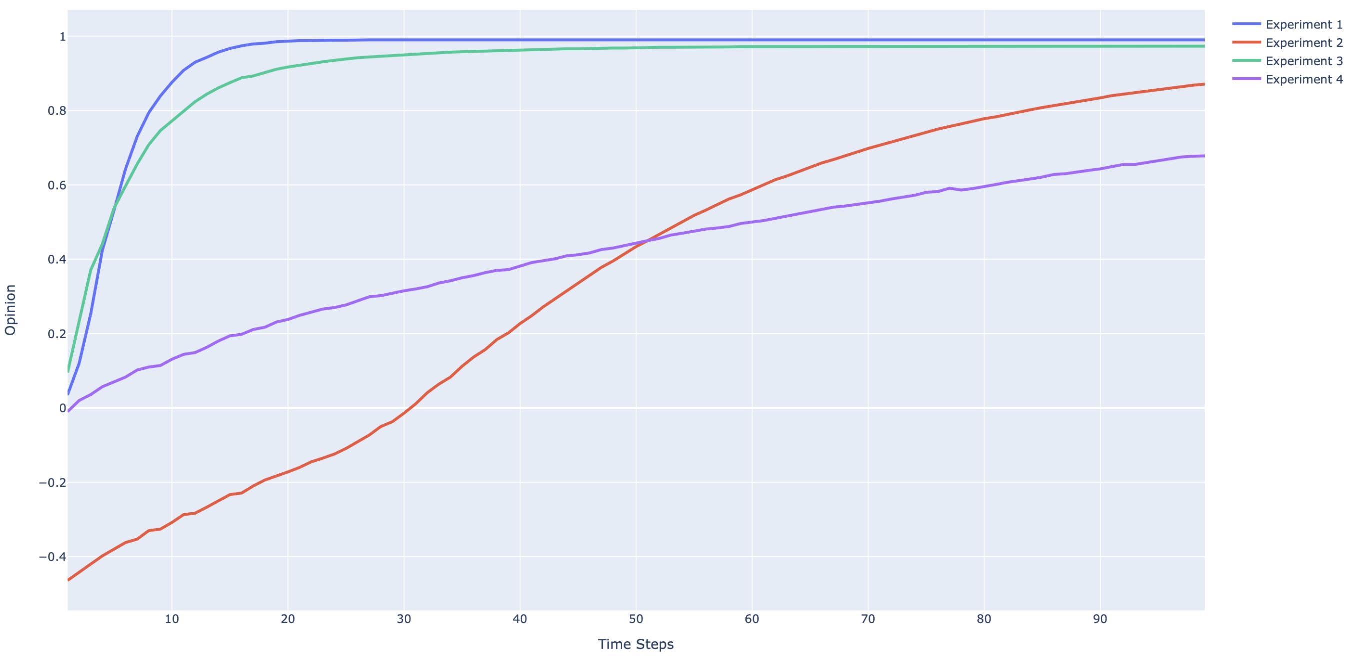

Figure 4.11: Role of influence on general Public opinion

5 Discussion

5.1 Project overview and discussion

The primary aim of this project was to develop an agent-based model of Twitter to simulate user interactions and explore opinion dynamics. Through a series of experiments, the model was tested against varying parameters to identify ones that have the greatest impact on opinion formation and polarization. The first set of experiments highlighted the importance of connectivity in preventing the formation of echo chambers and decreasing polarization. On the other hand, the second set of experiments emphasized the crucial role of diverse perspectives in combating extremism and avoiding the pitfalls of a closed community.

Range of endorsement vs opinion-based distancing:
Experiment 1 found that a higher endorsement index leads to a decrease in polarization due to wider network connectivity. Moreover, it concluded that as the endorsement index decreased, so did the connections between users. Similarly, running the model to test opinion distancing found the same behaviour. However, from the results presented in the previous section, it is evident that the endorsement index has a greater impact on the network than opinion distancing does as the number of connections dropped in the first experiment was far greater than those in the second. Between the two experiments we can observe that echo chamber behaviour starts to emerge when the beta index of the network goes below 6.93, this is a 24.3% drop from the original connectivity of the graph. These findings highlight the importance of network connectivity in reducing the effects of polarization and preventing echo chamber formation.

A theory proposed by political scientist John Zaller states that due to selective attention and acceptance, individuals alter their opinions to have them be consistent with their pre-existing beliefs and to those around them. The results of the model adhere to this principle. Additionally, the results suggest that higher connectivity leads to less polarization, this also aligns with the idea proposed by Zaller that individuals are more inclined to accept new information if it aligns with their perception. With higher connectivity, users perceive a farther range of opinions and are more likely to be accepting of them. [23].

Impact of influence vs opinion flexibility, polarization and public discourse:
With the second set of experiments, it was found that influential nodes have a significant role in shaping public opinion. Even when met with various factors such as users with rigid opinion boundaries, opposing opinions and public discourse. Influence impacted the general opinion of a community the most. Additionally, amongst the three varied parameters, public discourse and discussion had the most significant impact after influence in the information regulation within an online network. This set of experiments emphasises the importance of diversity, within the information regulated, in preventing the rise of extremism.

Looking at the current state of social media, we have observed a rise of influencers, these are individuals that possess the power to generate and spread information far on an online network as a result of having an audience [24]. In many ways this is a positive; it enables representation, sharing of ideas and raising awareness about topics in ways humans were unable to before the 'digital age'. However, this becomes a problem when the platform is abused to promote miss information or spread an extremist political agenda [25]. In the context of the model, we have observed the importance of retaining a diverse range of information bits within a network to prevent influential information from taking over public opinion. Hence, public discourse is imperative to maintain critical thinking skills at an individual level.

Reflection on visual and interactive aspects:
In addition to the model, this project aimed to produce animated visualizations and create an easy way to interact with the model and its results. This was accomplished with the use of the graphing library Plotly along with Flask. These elements are a crucial part of understanding the topic at hand. Interactive visualizations in particular are an imperative component of data analysis within a context such as this. The ability to view the changes on a network due to different factors is crucial in having a comprehensive understanding of the opinion dynamics in the network and concluding specifics from the runs of the model.

5.2 Critical Assessment and Potential Improvements

Though the current model accounts for many aspects of user interactions on Twitter networks there are limitations to be addressed. This model makes generalizations about user interactions and factors determining user connectivity. Therefore, it is unable to capture the nuances of real-world interactions. Furthermore, the current range of visualizations produced only reflect the experiments conducted and do not account for visualizations of tests on further parameters yet; Even though the model can accommodate testing against different parameters the visuals and the GUI cannot.

To improve the model's accuracy and increase its complexity in the future, it should be tested against a larger sample network. this study focuses on a smaller sample of network size. This would improve the calibration of the model. Additionally, testing the model with the use of a real network built from a following and friend networks from actual Twitter interactions could give us better insights into the network structure on actual social media platforms. Overall, the current model provides a valuable foundation in understanding these larger more complex concepts to what makes the public so polarized and how general public opinion is impacted.

5.3 Conclusion

The key aims of this study were met by developing a competent model created using Agent-Based Modeling. The model was fruitful in producing insights into factors that have the greatest impact on user interactions, polarization and public opinion. Firstly, it identified the degree to which endorsement and opinion distancing have an effect on network connectivity. The findings indicate a positive correlation between having higher network connectivity and reduced polarization within a network. Secondly, the results highlight the importance of diverse perspectives, open dialogue and critical thinking in preventing the dis-connectivity leading to echo chamber formation. In conclusion, this study makes a contribution to the field of information dynamics on social media by testing for and reiterating the importance of studying and addressing the issues related to online polarization and information flow of the digital age.

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