Modelling Polarisation on Social Media

Group E
Terry Huang s2144299,
Blythe Wray s2212924,
Gro Gisleberg s2180910,
Leo Kravtchin s1948094

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University of Edinburgh

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Abstract

Political polarisation is increasingly detrimental, challenging democratic decision-making and the ability of governments to adequately address other sustainability issues. It is argued that the internet intensifies this by accelerating the dissemination of polarising content and creating filter bubbles, which rarely expose individuals to other perspectives. To address this, we have implemented an agent-based model to identify thresholds and dynamics of social media polarisation, and provide insights into balancing online and offline interactions for reducing polarisation. We highlight the importance of sociological contexts in polarisation models. By incorporating an offline aspect to a model implementation inspired by related literature, we were able to imitate the globalisation of offline interactions and their influence to a wider range of agents. Although polarisation is not exclusive to the online sphere, our experiments prove that it is exacerbated by digitally exclusive means of communication, which aligns with the literature of the wider discourse.

Table of Contents

Chapter 1

Introduction

1.1 Project Motivations

Political polarisation is defined as a state where society's opinions are sharply divided, leading to the formation of partisan groups (Koudenburg and Kashima [2022]). This global issue poses a critical threat to democracies, undermining constructive dialogue and the exchange of diverse perspectives (Arbatli and Rosenberg [2021]). Although polarisation is not a new phenomenon, its intensification in recent years is creating growing concern (Arbatli and Rosenberg [2021]). Academics argue that it is exacerbated by the amplifying and fragmenting effects of the internet, as evidenced by events like Brexit and the Yellow Vest Movement, both of which have a solid foundation in online platforms and are linked to digital polarisation (Liu et al. [2022]).

The core of these difficulties is believed to be in the algorithms that filter content, generating 'filter bubbles' – defined as phenomena "whereby the ideological perspectives of internet users are reinforced as a result of the selective algorithmic tailoring of search engine results to individual users" (Chandler and Munday [2016]). As a result, users have limited exposure to a diverse range of opinions. Social media's effect on polarisation is argued by several scholars, such as Pariser [2011] and Sunstein [2017]. There has been a significant amount of research on the subject in the past decade; yet, the degree to which social media personalisation induces polarisation remains uncertain (Arora et al. [2022]). This prompts important questions; Do these personalisation tools enhance connectivity, or exacerbate divisions among us? What is the typical response of people to being faced with conflicting perspectives? In the pressing urgency this has for sustainable development and for the informed decision of policy makers, we aim to contribute by further researching this phenomenon and these questions.

1.2 Project Aims

Our project aims to employ agent-based modelling (ABM) to investigate how algorithms regulating feed outputs on social media platforms contribute to the polarisation of public opinion and societal divisions. Agent-based modelling is a simulation technique that uses individual entities, called agents, to recreate real-life interactions and scenarios within a bounded environment based on simple parameters and scales. Each agent acts autonomously, but collectively their interactions produce complex behaviour in the wider model. Agent-based models (ABMs) have proven effective in various fields, such as ecology (Zhang and DeAngelis [2020]), economics (Axtell and Farmer [2022]), and engineering (Araya [2020]). They are particularly useful in the context of our research, by allowing simulation of societal dynamics over extended periods of time, and the testing of various parameters, where long-term empirical research often is unviable (Puniya et al. [2024]). For the context of our study on social media algorithms and their effect, an ABM is well-suited, by allowing a focus on structural variables established by platforms and the overarching societal characteristics that contribute to opinion polarisation.

Our objective is to comprehend the dynamics of thought division or unification and the influence of these platforms on public conversation. By using ABM, we can dynamically model users' various opinions and better understand how micro-level interactions can drive macro-level polarisation trends. We may achieve this by assigning each agent a distinct opinion and the likelihood of that opinion being altered, and observing how they may evolve through interactions within the established ecosystem. By doing this, we might draw insight insight into the online social climate on a smaller and more comprehensible scale.

We use NetLogo to create and implement our agent-based model. NetLogo is a platform by Northwestern University[1], specifically designed to model environments involving multiple agents, using a unique coding syntax composed of commands and reporters. A command directs an agent to execute a task that produces a predetermined outcome, while a reporter involves instructions for calculating a value that the agent then returns as a value output. Inputs can also be incorporated into these functions to affect the computation of the action or result (Railsback [2019]).

1.2.1 Research Questions

Using the modelling formulae presented by Keijzer et al. [2024], we build upon this framework to formulate the following research questions:

- **RQ1** Is there a threshold in bubble size that transitions the system from a state of various viewpoints to one of significant polarisation, especially while sustaining a fluctuating yet stable population size?
- **RQ2** How does altering the proportion of online agents affect the overall opinion dynamics of the system, in light of social theories related to online communication and group behaviour?
- **RQ3** How does the frequency of offline interactions compared to online interactions influence the stability and variability of opinion states?

[1] https://ccl.northwestern.edu/netlogo/

Chapter 2

Background

2.1 Foundational Model Description

Our approach draws inspiration from a foundational model created by Keijzer et al. [2024], which employs agent-based modelling (ABM) to examine the role of algorithm-driven 'filter bubbles' on social media platforms in facilitating polarisation. The foundational model shows how algorithms can hinder interactions between various social groups, whilst reinforcing homogeneity within groups. In the real world, material in users' feeds is personalised depending on their previous interactions and interests. The foundational model emulates this by replicating automated content curation, thereby reinforcing existing biases and constraining exposure to alternative perspectives.

2.2 Agents and how Opinions Change

Each agent in the Keijzer et al. [2024] model represents a distinct user on a social media network. Agents are initialised with a random opinion ranging from 0 to 1, and assigned to one group. Opinion distribution and group membership are independent variables upon initialisation. The interactions between agents can lead to two distinct outcomes based on their initial similarity of opinion. Agents within the same group influence each other differently than they influence agents from other groups, leading to distinct interaction dynamics between and within groups. Depending on the similarity of the agents' original opinions and their group affiliations, these interactions can lead to increased agreement (assimilative influence) when opinions are aligned, or increased disagreement (repulsive influence) when opinions are of significant difference.

2.3 Filters and Interactions

Filter bubbles and interaction rules are important concepts to understand. A filter bubble is a protective barrier that exclusively presents information and opinions that align with your existing beliefs or preferences. This occurs because websites and social media platforms employ algorithms to choose what content to display depending on your previous behaviour. This manipulation of exposure can profoundly deepen societal divisions, leaving us unaware of the broader spectrum of ideas and beliefs that shape society as a whole.

Sunstein [2017] argues that the rules governing online interactions significantly shape the nature of discussions. When individuals engage exclusively with like-minded peers, it cultivates online echo chambers [1] where ideas are endlessly reinforced without critique, reducing exposure to differing perspectives and making it more challenging to embrace new or opposing viewpoints.

The Keijzer et al. [2024] model incorporates the concept of filter bubbles by restricting each agent's interactions to those who fall within their filter-bubble span. They present users with content aligned with their prior preferences, hence diminishing the likelihood of encountering diverse perspectives.

The interaction procedure within the foundational model operates as follows: whenever a random ”receiving” agent engages, the model selects a ”sending” agent from within the predetermined span of the receiver's filter bubble. The size of this bubble, an adjustable parameter within the model, represents the extent of exposure diversity. Smaller bubble sizes result in less exposure to differing opinions, potentially exacerbating societal divisions. The model also includes mechanisms to simulate how agents handle incoming information. Parameters within the model dictate the thresholds beyond which an agent rejects new information and begins to actively oppose it. This dynamic reflects the phenomenon examined in Flache et al. [2017], highlighting how social influence can result in persistent divisions when the diversity of exposure is limited.

2.4 Polarisation Metrics

Keijzer et al. [2024] evaluates polarisation using three key indicators:

Spread: The range between the highest and lowest opinions in the population, reflecting overall opinion variety.

$$\text{Spread} = \max(o_i) - \min(o_i) \tag{2.1}$$

Dispersion: The average distance of opinions from the average:

$$\text{Dispersion} = \frac{1}{N}\sum_{i=1}^{N} |o_i - \bar{o}| \tag{2.2}$$

where $\bar{o}$ is the mean opinion of the population.

Coverage: The proportion of the opinion spectrum that is covered by unique opinions.

$$\text{Coverage} = \frac{\text{Number of unique opinions}}{\text{Total possible opinions in [0,1]}} \tag{2.3}$$

[1] Note that our research uses the terms ”filter bubbles” and ”online echo chambers” interchangeably

Entropy in Natural Language Processing measures the unpredictability and diversity of word sequences (Jurafsky and Martin [2009]). In a similar vein, when applied to opinions over time, entropy could be used to gauge the variety and unpredictability of opinions, highlighting whether opinions, and their respective discussions, are widely diverse or narrowly homogeneous. Johnson [1940] found that those with unconventional opinions are confident in expressing them, suggesting that entropy may be lower in social media due to viewpoint predictability and homogeneity. Johnson's research indicated that beliefs consistent with group norms are spoken with greater confidence, facilitating the establishment of online echo chambers. Environments marked by reinforced similar perspectives are likely to have diminished diversity in opinions, a condition comparable to low entropy. Opinion entropy can therefore be used to disclose whether debates are broad and dynamic or confined and polarised, making it a useful metric for evaluating how content algorithms affect social media polarisation.

Entropy: A measure of randomness of a given agent's opinion at a point in time.

$$\text{Entropy} = -\sum_{i=1}^{k} \frac{n_i}{N} \log\left(\frac{n_i}{N}\right) \tag{2.4}$$

where n_i is the number of agents in the i-th opinion interval, N is the total number of agents, and k is the number of opinion intervals. A higher entropy value indicates a more evenly distributed range of opinions.

2.5 Implications and Social Media Polarisation Insights

Keijzer et al. [2024] demonstrates how algorithmic biases on social media platforms might influence the dynamics of opinion formation, lending support to the 'personalisation-polarisation hypothesis.' Coates [2020] expands on this by developing intervention algorithms that strategically adjust network connections to reduce polarisation. Coates introduces methodologies, including the 'network temperature' metric, to evaluate the effectiveness of these interventions in promoting diversity in opinion exposure. The findings suggest that even minor adjustments, such as reducing content limitations, can substantially decrease polarisation by broadening user exposure to varied opinions. Furthermore, Deffuant et al. [2002] found that increased engagement with diverse beliefs reduces polarisation but may also curtail activity among users who shy away from conflicting points of view. Adjusting social media platform algorithms to promote a wider diversity of information could thus be an effective strategy to counteract polarisation, improving social media platforms' resilience against divisive content.

2.6 Increasing Affective Polarisation

Affective polarisation refers to the manifestation of polarisation on the individual's level and how their group affiliation shapes an individual's interactions towards others, unlike general polarisation, which focuses on the macro-level stances of the wider population and the tension between these groups (Phillips [2022]). Affective polarisation is characterised by the following behaviour:

- Warmth and favouritism towards members of one's own party (in-group).
- Hostility and distrust towards members of an opposing party (out-group).

Furthermore, Phillips [2022] finds that affective polarisation increases as people age due to increased partisan strength, cognitive changes, social role transitions, and enhanced partisan sorting. The cumulative effects of affective polarisation at the individual micro-level, particularly as these dynamics reinforce themselves over time, deepen divisions and amplify polarisation at the societal level (Phillips [2022]). Inspired by this, our model implements a factor of increased affective polarisation as agents age, reflecting how this phenomenon possibly shapes the polarisation trajectory in wider society.

2.7 Social Identity

An important aspect of affective polarisation is social identity, as individuals lay the foundation of their trust and distrust in others based on whether they categorise themselves in the same group (Phillips [2022]). Individuals do not merely see themselves as part of a group but construct their own individual identity through this in-group affiliation; their own identity and opinion actively being shaped by that of other in-group members.

While social identity theory argues for individuals' loyalty to their affiliated in-group members, it also highlights the multifaceted nature of individual identity, describing it as a "fusion of multiple socially defined cleavages such as religion, ethnicity, etc." Arora et al. [2022][p.7]. Assigning agents to one individual group, like in the Keijzer et al. [2024] model, can therefore be considered too simplistic when accounting for these complex real-world dynamics. It is therefore important to incorporate the possibility of agents belonging to multiple groups, with varying strengths of affiliation while still reflecting in-group favouritism.

2.8 The Role of Social Cohesion in Urban and Rural Polarisation

Avery et al. [2021] finds that rural communities exhibit higher levels of social cohesion compared to urban communities. In rural areas, people are more likely to help each other, trust each other, and keep a close-knit sense of community. All of these things can help people get along better with each other and lessen polarisation. In contrast, urban social areas often have lower levels of social cohesion (Avery et al. [2021]), which might lead to more selective interactions and higher polarisation.

These insights illustrate the importance of considering spatial and social contexts when addressing polarisation when it comes to developing a model representative of the real-world. The results by Avery et al. [2021] show how important it is to have offline interactions that are limited by space. It is therefore advantageous to think about how differences in social cohesion affect both offline and online interactions, eventually creating greater societal divides.

Feature	Keijzer's Model	Our Model
Agents have opinions ranging from 0 to 1	✓	✓
Influence weight computed as $(1-\gamma\times\|\Delta\|)$	✓	Modified
Agents are assigned to a group	✓	✓
Multiple group memberships		✓
Agents have online/offline status		✓
Agents age		✓
Agents move in space		✓
Physical interactions based on proximity		✓
Opinion update considers group similarity	✓	✓
Opinion update considers group strengths		✓
Agent birth and death		✓
Adjusted birth rate based on young agent proportion		✓
Polarisation measures: spread, dispersion, coverage	✓	✓
Polarisation measure: entropy		✓
Plots for polarisation measures	✓	✓
Bubble size parameter in online interaction	✓	✓
Agent opinion tends toward extremity as they age		✓
Agents' group strengths increase over time		✓
Death probability increases with age		✓
Alpha parameters: α_0, α_1, α_2	✓	Modified
Gamma parameters: γ_0, γ_1		✓

Table 2.1: Comparison of Features between Keijzer's Model (foundational) and Our Model

Chapter 3

Implementation

We initialise a population of **num-agents** agents, each assigned an opinion o_i sampled from a uniform distribution between 0 and 1, representing a range of ideological positions. Each online agent's social media interactions are shaped by the similarity of their opinions to those of other online agents, with the degree of interaction moderated by a personalisation algorithm that simulates exposure within a social network. The likelihood of interaction and the degree of filter bubbles are influenced by the **bubble-size** parameter, which dictates how selective the social media algorithm is in permitting users interacting based on opinion similarity. Adjustments to these interactions are driven by intricate aspects such as the agent's age, how much they associate with a group, and the dynamics of their articulated opinions and affiliations within the simulation.

3.1 Temporal Framework in Detail

We apply a multi-fasciated temporal framework to simulate the complex flow of social interactions and demographic changes. Each layer, as illustrated in Figure 3.1, is fine tuned to simulate different events, ensuring that the model captures both the fast pace effect of daily interactions and the slow pace of demographic shifts.

3.1.1 Online Interaction Dynamics

Online interactions occur at the finest granularity in the model, simulating the almost instantaneous nature of online interactions and communication. These interactions are designed to emulate the behaviour observed in real-world social media platforms, where users engage based on perceived similarity. At each simulation time step t, the following steps are performed as described in the Keijzer et al. [2024] model:

- **Select a Receiver:** One agent is randomly chosen from the population to act as the receiver for this time step's interaction.
- **Determine Bubble Size:** Calculate the bubble size based on the **bubble-size** parameter, which defines the fraction of agents that can interact based on opinion similarity.

- **Exclude the Receiver:** Exclude the receiver from the list of potential senders to prevent self-interaction.
- **Calculate Opinion Differences:** Compute the absolute differences in opinion between the receiver and each potential sender.
- **Sort by Opinion Similarity:** Sort the potential senders by their opinion differences from most to least similar to the receiver.
- **Select Interaction Bubble:** Select a subset of agents from the sorted list, limited by the bubble size, to form the interaction bubble.
- **Pick a Sender:** Randomly choose one agent from the interaction bubble to act as the sender.
- **Interaction Effect:** The selected sender influences the receiver's opinion, adjusted by factors such as group similarities and individual influence strengths.
- **Update Receiver's Opinion:** Update the receiver's opinion based on the interaction effect, ensuring it remains within the bounds of 0 to 1.

The lack of spatial constraints for online interactions is a deliberate design choice as it is meant to reflect the global reach and lack of bounds of social media. Therefore, opinion alignment plays a much more important role in forming and maintaining connections.

3.1.2 Offline Interaction Cycles

We begin to augment this foundational model by incorporating offline interactions to account for rural social cohesion, as discussed in Section 2.6, and explore how this interacts with online dynamics. Offline interactions are less frequent than online interactions, as real-world human engagements are rarer and more physically localised. Offline intervals every T_{offline} time-steps represent steps where agents can engage in an 'in-person' manner with those in their vicinity. At each $T_{offline}$ interval:

- **Agent Movement:** All agents adjust their physical location in the simulation environment. Each agent randomly rotates and moves forward by a predefined distance, simulating random movement within their space.
- **Identify Nearby Agents:** A randomly chosen receiver agent identifies other agents within a specified interaction radius, excluding themselves to ensure no self-interactions occur.
- **Identify The Sender:** A random agent from those nearby (within the interaction radius) is selected as the sender.
- **Calculate Opinion Influence:** The influence of the sender on the receiver is calculated based on the difference in their opinions, the similarity of their group affiliations, and other model-specific parameters.
- **Update Opinions:** The receiver's opinion is updated based on the calculated influence, with checks to ensure the new opinion remains within the range of 0 and 1.

The outcomes of offline interactions can influence agents' future online interactions by reinforcing or diminishing social clusters within the simulation. We define offline interactions as those that are characterised by their spatial limitations, confined within a radius $R_{\text{interaction}}$ around the receiver. This radius delineates the boundary within which potential interaction partners can be found, simulating scenarios such as living in the same neighbourhood or participating in social gatherings. The infrequent timing of offline interaction cycles mirrors the reality that face-to-face meetings occur far less often than online interactions, allowing the model to balance the continuous influence of online interactions with periodic offline dynamics.

3.1.3 Demographic Adjustments

To account for population-wide demographic processes such as ageing, births, and deaths, we add to our model by incorporating a broader temporal scale of every (T_{ageing}) time-steps. This allows the model to take long-term trends into consideration when looking at societal evolution. At each T_{ageing} interval:

- **Increment Agent Age:** All agents increment their age by 1 unit, simulating the passage of time within the simulation.
- **Handle Agent Deaths:**
  - Agents whose age exceeds the maximum allowed age (**max-age**) are removed from the population.
  - A probabilistic death process occurs where older agents have an increased likelihood of dying, based on the model's age-related mortality factor.
- **Handle Agent Births:**
  - If the population size is below the carrying capacity (**carrying-capacity**), new agents are created to maintain population stability.
  - New agents inherit a slightly modified opinion from existing agents or are assigned random opinions if no existing agents are available.
- **Adjust Group Strengths:**
  - Each agent's group strengths are adjusted to increase towards their maximum possible values (e.g., 1), simulating stronger affiliation over time.
  - Ensure group strengths remain within the range of 0 to 1.
  - This process links to affective polarisation (as discussed in Section 2.6) by intensifying emotional attachments to groups, reinforcing in-group biases, and widening the gap between opposing groups over time.
- **Opinion Extremity Increase:**
  - Agents' opinions are adjusted to move towards the extremes (0 or 1), depending on whether their current opinion is above or below 0.5.
  - Ensure that opinions remain within the bounds of 0 to 1 after adjustment.

- **Adjust Birth Rate:** The birth rate is dynamically adjusted based on the proportion of younger agents (e.g., those aged below 10) and the number of agents currently alive. This is to ensure population balance and demographic diversity.

The results of interactions over time may influence the agents' future. Ageing impacts an agent's characteristics, including vulnerability to persuasion and inclination towards extreme opinions. As agents age, their perspectives tend to gravitate towards ideological extremes, exacerbating affective polarisation by reinforcing allegiance to in-groups and cultivating animosity towards out-groups. This tendency exacerbates divisions, diminishing the probability of productive engagement among agents with divergent viewpoints.

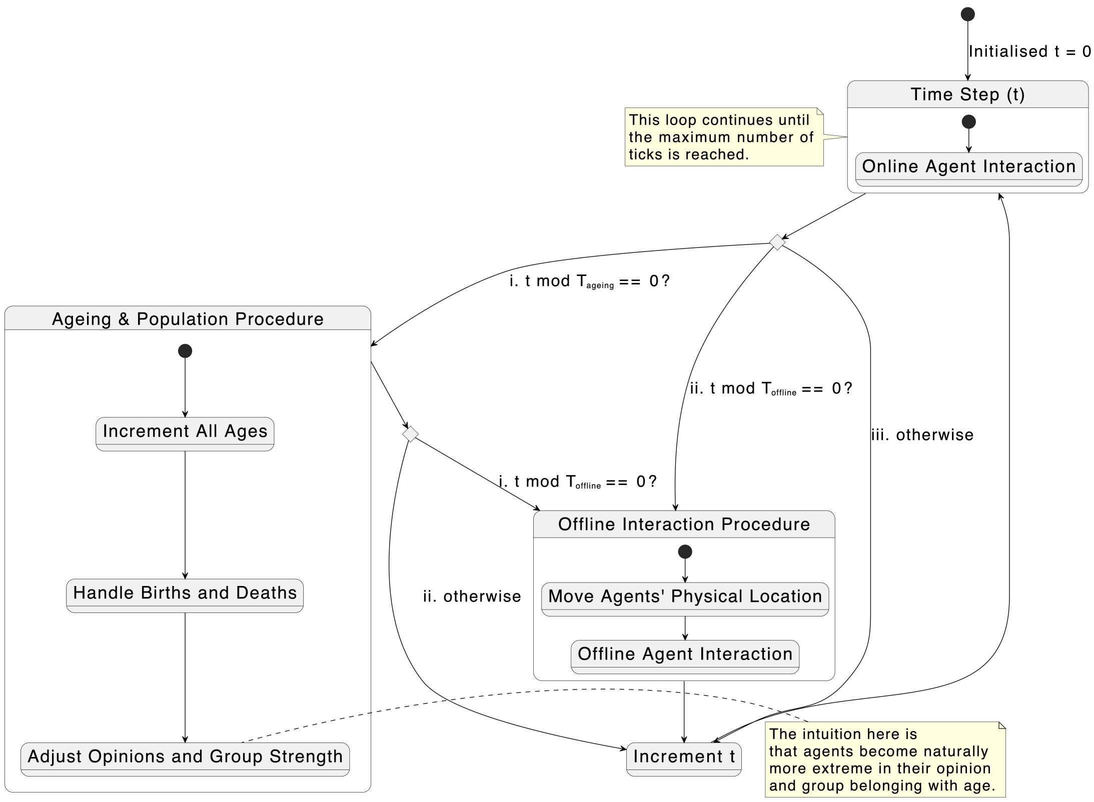

Figure 3.1: Temporal steps in the simulation model, showing how agents interact online and offline, age, and adjust their opinions and group strength over time.

3.2 Spatial and Movement Considerations

Spatial dynamics are integral to the offline aspects and the physical bounds of real-world communities. Each agent is positioned in a 2D bounded space where movement and proximity are used to determine offline engagement:

- Positioning and Mobility: Agents spawn with randomly assigned positions within the defined area. Movements are made every (T_{offline}) time-steps are modelled as random within a set distance (D_{move}), as real world people have limited mobility within these local communities or neighbourhoods. Throughout the runtime of the simulation, this creates a dynamic yet contained reshuffling of interaction partners.

Agent Movement (All Agents):

$$\text{Position}_{i,t+T_{\text{offline}}} = \text{Position}_{i,t} + D_{\text{move}} \cdot \mathbf{u}_i \tag{3.1}$$

Where $\mathbf{u}_i$ is a unit vector in a random direction and D_{move} is a parameter that depicts how far an agent moves each $T_{offline}$ interval.

- Proximity-Driven Interactions: The ability to perform offline interactions is limited to agents within a specified radius; agents outside this radius cannot interact. This spatial constraint introduces a key difference between offline and online dynamics, where online interactions are not restricted by physical distance, while offline interactions occur only between agents within a defined proximity.

  The difference in online and offline interactions is as follows:

  Interaction Partner Selection:

  - **Online Interactions**: Select partner j based on opinion similarity (filter bubble) from another online agent.
  - **Offline Interactions**: Select partner j randomly from agents within radius $R_{\text{interaction}}$ where $R_{interaction}$ is a parameter that decides how far apart two agents must be in the environment for them to be able to communicate in-person.

By using these spatial factors, the model can explore trends and phenomena like the clustering of opinions in geographically isolated groups, contrasting with the global homogenisation or polarisation driven by the online sphere.

3.3 Population Dynamics: Beyond Static Agents

Our real-world population is not static; it grows, shrinks, and evolves over time. To best reflect this, we augment the Keijzer et al. [2024] model by integrating a continuously changing population, to better represent the changing demographics observed in real-world populations.

3.3.1 Ageing and its Effects

Ageing agents become less susceptible to influence and change, this is to reflect our research that implies that opinions tend to 'lock in' with age. Additionally, older agents' opinions lean towards the extremities.

3.3.2 Mortality and Replacement

The likelihood of an agent's death increases linearly with age, which simplifies the representation of mortality trends without employing a complex logistic function. To maintain a stable population size for consistent analysis and to ensure the simulation can run its full course, we adjust the birth rate based on the difference between the maximum population limit and the current number of agents. This approach avoids directly replacing deceased agents, allowing us to focus on the natural dynamics of population changes without the population growing and shrinking drastically.

3.3.3 Stabilising The Population Size

In our model, two key parameters govern the population dynamics: **num-agents** and **carrying-capacity**. The **num-agents** parameter sets the initial number of agents at the beginning of the simulation, establishing the starting population size. In contrast, the **carrying-capacity** parameter represents the maximum sustainable population size that the environment can support without leading to resource depletion or detrimental overcrowding.

We have chosen to implement a dynamic birth rate that depends on the difference between the **carrying-capacity** parameter and the current number of alive agents to maintain a consistent population size while preserving the natural flow of births and deaths. This methodology enables us to concentrate purely on opinion dynamics in a controlled setting, so eliminating the influence of concealed variables associated with sizeable fluctuations in population size.

Utilising a dynamic birth rate instead of a simple replacement method strikes a balance between avoiding artificial limitations and capturing genuine population variations, ensuring the simulation reflects a more realistic human lifespan. This design decision corresponds with our experimental objectives, as we are not examining the impact of population size on dynamics but rather the evolution and polarisation of opinions within a stable population.

3.4 Agent Ageing Formulae

First, we define the number of births as the proportion of potential new agents that can be accommodated before the carrying capacity is reached. (i.e. We set the birth rate based on how the difference between the carrying capacity and the current number of alive agents decreases.)

Births:

$$B_{t+T_{ageing}} = b_{t+T_{ageing}} \left(C - N_{t+T_{ageing}}\right) \tag{3.2}$$

Where:

- $B_{t+T_{ageing}}$ is the number of births at time $t + T_{ageing}$.
- $b_{t+T_{ageing}}$ is the dynamically adjusted birth rate at time $t + T_{ageing}$.
- C is the **carrying-capacity**.
- $N_{t+T_{ageing}}$ is the current population size at time $t + T_{ageing}$.

Next, we focus on the proportion of the population who are under 10 years old. If this proportion is more than $r_{threshold} = 0.2$ of the population, we lower the birth-rate gradually. Else, we slowly increase it back up little by little.

New agents are initialised similarly to the initial population but inherit opinions from existing agents with slight randomness to prevent saw-toothing when it comes to the spread metric.

1. **Calculate Young Ratio (Subset of population under 10 years):**

$$r_{\text{young},t+T_{ageing}} = \frac{N_{\text{young},t+T_{ageing}}}{N_{t+T_{ageing}}} \tag{3.3}$$

2. **Adjust Birth Rate:**

$$b_{t+T_{ageing}} = \begin{cases} \max\left(b_{\text{lower}}, b_{\text{normal}} - (r_{\text{young},t} - r_{\text{threshold}})\right) & \text{if } r_{\text{young},t} > r_{\text{threshold}} \\ \min\left(b_{\text{normal}}, b_{\text{lower}} + (r_{\text{threshold}} - r_{\text{young},t})\right) & \text{if } r_{\text{young},t} \leq r_{\text{threshold}} \\ b_{\text{default}} & \text{if } N_t = 0 \end{cases} \tag{3.4}$$

where:

- b_{lower} is the lowered birth-rate. We have set it to 0.1
- b_{normal} is the normal birth-rate. We have set it to 0.2
- $b_{default}$ is the birth-rate when there are no agents. We have set it to 0.25
- $r_{threshold}$ is the proportion of young agents that needs to be met for birth-rate to decrease. We have set it to 0.2
- N_t is the current population size at at time t.

This adjustment ensures that the birth rate decreases when there are too many young agents and increases when there are too few. Appendix B explains how we have fit the model to run with these values.

The ageing process is also carried out every T_{ageing} time steps. All agents age at the same time.

Ageing Process:

$$A_{i,t+T_{ageing}} = A_{i,t} + 1 \tag{3.5}$$

Where $A_{i,t}$ is the age of agent i at time t.

To model affective polarisation, we increase group affiliation every T_{ageing} time steps.

Group Affiliation Strength Adjustment:

$$s_{i,k,t+T_{ageing}} = s_{i,k,t} + (1 - s_{i,k,t})\delta_s \tag{3.6}$$

Where:

- $s_{i,k,t}$ is the non-zero strength of agent i's membership in group k at time t.
- δ_s is the group strength increase rate.

Similarly, we do the same for opinion extremity.

Opinion Extremity Adjustment:

$$o_{i,t+T_{ageing}} = \begin{cases} o_{i,t} + (1 - o_{i,t})\delta_o & \text{if } o_{i,t} > 0.5 \\ o_{i,t} - o_{i,t}\delta_o & \text{if } o_{i,t} \leq 0.5 \end{cases} \tag{3.7}$$

Where δ_o is the opinion extremity increase rate.

Lastly, at each T_{ageing} time steps, agents have a probability of dying. This probability increases as they age.

Probabilistic Death:

$$p_{\text{death},i,t+T_{ageing}} = p_0 + \left(\frac{A_{i,t+T_{ageing}}}{A_{\max}}\right)\delta_d \tag{3.8}$$

Where:

- $p_{\text{death},i,t+T_{ageing}}$ is the probability that agent i dies at time $t + T_{ageing}$.
- p_0 is the base death rate.
- δ_d is the age death factor.
- $A_{i,t+T_{ageing}}$ is the age of agent i at time $t + T_{ageing}$.
- $A_{\max}$ is the maximum age parameter.

Agents die with probability $p_{\text{death},i,t+T_{ageing}}$ at each ageing step. Agents automatically die if $A_{i,t+T_{ageing}} \geq A_{\max}$.

3.5 Opinion Influence Mechanism

The opinion influence mechanism is the main meat of the model, as it determines how both online and offline interactions affect individuals' opinions. The formulae we use are adapted from that used in the foundational model to best replicate observed psychological and social behaviours.

3.5.1 Opinion Similarity

The level of influence between two interacting agents is calculated using the similarities in their opinion. This relationship is defined by a non-linear function that puts emphasis on the psychological tendency for individuals with already similar opinions to have stronger mutual influence:

- Non-linear Modulation: Influence strength decreases as opinion differences grow, because there is a reduced willingness to be influenced by those with divergent views.
- Asymmetric Update Rules: The level of opinion change is determined by the receiving agent's susceptibility, which will vary across age groups and other demographics.

3.5.2 Group Affiliation

Group memberships amplify the influence of similarity:

- Shared affiliations (e.g., political parties, cultural groups) increase the influence weights; real-life observations that individuals are more easily persuaded by those within their identity groups.
- Membership strength is typically characterised as continuous rather than binary, as we want a nuanced representation of varying levels of belonging. Our model adds a boolean parameter for **binary-group-membership?** so that it has the flexibility to explore both options.

3.6 Group Membership Dynamics

Group membership is a vital part of the model, encapsulating the social identities that influence behaviour and opinion. We further extend our model by allowing agents to belong to multiple groups, with the following considerations:

- We assign a many-to-many cardinality relationship between agents and groups with the use of **avg-num-groups-per-agent** and **sd-num-groups-per-agent** parameters to imitate normally distributed group belonging.
- Strength and Overlap: How much a group makes up an agent's identity varies across agents and groups, since it's not a monolith and there will be differing levels of commitment and affiliation. Overlapping memberships allow for interactions with diverse identity boundaries.
- Dynamic Adjustments: Group memberships can evolve and grow with age. How quickly this may happen will be determined by the **group-strength-increase** parameter we introduced previously.

In the presence of K groups to which agents may belong, each agent's group affiliation strengths will be represented as a vector including K components, with each component being a float within the range of 0 to 1. We may assess the similarity $\delta_{e,ij}$ of these agent group belonging vectors by calculating the dot product and normalising it by the number of components K (ie. cosine similarity), yielding a comparable similarity range between 0 and 1 for all agent interactions.

Group Membership Similarity:

$$\delta_{e,ij} = \frac{1}{K} \sum_{k=1}^{K} s_{i,k} s_{j,k} \tag{3.9}$$

This calculates the average product of group membership strengths between agents i and j, resulting in a value between 0 and 1.

3.7 Integration and Calibration

Once we bring all these components together, the ABM is calibrated to simulate diverse scenarios:

- Key parameters, such as P_{online} (**online-agent-percentage**), $R_{\text{interaction}}$ (**interaction-radius**), and D_{move} (**move-distance**), are ran with a range of values to observe their effects on system behaviour.
- Empirical Validation: Whenever possible, real-world data on opinion dynamics, online interaction patterns, and demographic trends are used to validate the model's outputs.

This calibration process helps to refine the model parameters and ensure that the simulations closely mimic real-world phenomena.

Opinion Update Equation This occurs every time step t for online interaction and again every $T_{offline}$ time-steps for offline interactions:

$$o_{i,t+1} = o_{i,t} + \Delta o_{i,t} \tag{3.10}$$

Where:

- $o_{i,t}$ is the opinion of agent i at time t.
- $\Delta o_{i,t} = \alpha_{\text{total}} \omega_{ijt}(o_j - o_{i,t})$ is the change in opinion based on the influence from agent j.

Of course the influence of agent j on agent i will rely on agent i's receptiveness to new information.

Total Influence Susceptibility:

$$\alpha_{\text{total}} = \alpha_0 + \alpha_1 \delta_{e,ij} + \alpha_2 s_i \tag{3.11}$$

where:

- α_0 is the baseline susceptibility parameter.
- $\alpha_1 \delta_{e,ij}$ adjusts susceptibility based on group membership similarity between agents. As shown in Equation 3.9, group similarity $\delta_{e,ij}$ is calculated as the cosine similarity of strength vectors of agents i and j. α_1 is therefore a parameter that regulates the impact of social group dynamics based on the degree of similarity between interacting agents.
- $\alpha_2 s_i$ on the other hand scales susceptibility based on agent i's own group membership strength, where s_i is the average strength across all groups for agent i:

$$s_i = \frac{1}{K} \sum_{k=1}^{K} s_{i,k} \tag{3.12}$$

To ensure a comprehensive understanding of how agents influence one another, it is also crucial to consider the mechanism by which influence is weighted:

Influence Weight Function Adjusted for Group Membership:

$$\omega_{ijt} = 1 - \gamma_0 |o_j - o_{i,t}| + \gamma_1 (1 - \delta_{e,ij}) |o_j - o_{i,t}| \tag{3.13}$$

where:

- γ_0 serves as a factor for controlling the influence of absolute differences in opinion, lessening the weight of influence as dissimilarity increases.
- When there is less similarity in group membership and affiliation between two agents, γ_1 makes the impact weight stronger. (i.e. When there is more diversity among group members, it makes the influence effects stronger.) It is crucial to observe that when $\gamma_1 < 0$, the effects are reversed.

This weight function incorporates both the disparity in opinions and the similarity in group memberships, altering the influence according to the alignment of the agents' group affiliations. The model seeks to replicate authentic social dynamics by coordinating these elements, whereby both opinion diversity and social cohesion are important.

Chapter 4

Experiments Setup

This chapter explores how we set up our experiments after the implementation discussed in chapter 3. We then obtain the findings as shown in the next chapter 5. The setup was selected to verify the model's correctness and for further results observations.

4.1 Baseline Experimental Parameters

The baseline experimental setup uses the following parameters to achieve stable and expected results. Afterwards, we can then analyse impacts of specific parameters using a dedicated experiment consisting of three additional sub-experiments each to test different values per chosen parameter. The results of the first, sixth, and seventh experiments are later explored in chapter 6.

Unless stated otherwise, all experiments are conducted with these default baseline parameters:

- **Model Dynamics**
  - num-agents: 350
  - carrying-capacity: 375
  - max-ticks: 5000
- **Group Settings**
  - bubble-size: 25
  - num-groups: 6
  - multiple-group-membership: On
  - binary-group-membership: Off
  - avg-num-groups-per-agent: 2
  - sd-num-groups-per-agent: 1
- **Agent Ageing**
  - ageing-interval: 300
  - max-age: 100
  - base-death-rate: 0.0002
  - age-death-factor: 0.02
  - group-strength-increase: 0.05
  - opinion-extremity-increase: 0.01
- **Birth-rate**
  - Dynamically assigned throughout model

- **Online-Offline Setup**
  - offline-interaction-interval: 50
  - online-agent-percentage: 90%
  - interaction-radius: 1
  - movement-distance: 1
- **Opinion Influence Parameters**
  - alpha0: 0.20
  - alpha1: 0.50
  - alpha2: 0.3
  - gamma0: 1.50
  - gamma1: -0.50

4.2 Experiment 1: Varying Bubble-size

The first experiment is to test the impact of varying the bubble-size parameter through the following sub-experiments:

- Experiment 1.0: Baseline (bubble-size 25)
- Experiment 1.1: Changed bubble-size to 50
- Experiment 1.2: Changed bubble-size to 75
- Experiment 1.3: Changed bubble-size to 100

4.3 Experiment 2: Changing Number of Groups

This experiment is changing the number of groups and is conducted using three subexperiments:

- Experiment 2.0: Changed num-groups to 2
- Experiment 2.1: Changed num-groups to 4
- Experiment 2.2: Baseline (num-groups 6)
- Experiment 2.3: Changed num-groups to 8

4.4 Experiment 3: Group Membership Variations

The group membership variations are tested in this experiment:

- Experiment 3.0: Baseline (multiple group membership to On; binary membership is Off)
- Experiment 3.1: Changed multiple group membership to Off; Changed binary membership to On
- Experiment 3.2: Changed multiple group membership to Off; Changed binary membership to Off
- Experiment 3.3: Changed multiple group membership to On; Changed binary membership to On

4.5 Experiment 4: Varying Group Strength Increase

The fourth experient is to observe the impact of changing the group strength increase as follows:

- Experiment 4.0: Baseline (group-strength-increase 0.05)
- Experiment 4.1: Changed group-strength-increase to 0.1
- Experiment 4.2: Changed group-strength-increase to 0.15
- Experiment 4.3: Changed group-strength-increase to 0.2

4.6 Experiment 5: Varying Opinion Extremity Increase

The opinion extremity increase changes are observed through this experiment:

- Experiment 5.0: Baseline (opinion-extremity-increase 0.01)
- Experiment 5.1: Changed opinion-extremity-increase to 0.02
- Experiment 5.2: Changed opinion-extremity-increase to 0.03
- Experiment 5.3: Changed opinion-extremity-increase to 0.04

4.7 Experiment 6: Changing Online Agent Percentage

The sixth experiment is to change the online agent percentags through the following sub-experiments.

- Experiment 6.0: Baseline (online-agent-percentage 90%)
- Experiment 6.1: Changed online-agent-percentage to 70%
- Experiment 6.2: Changed online-agent-percentage to 50%
- Experiment 6.3: Changed online-agent-percentage to 30%

4.8 Experiment 7: Varying Offline Interaction Interval

The final experiment is changing the offline interaction intervals as follows:

- Experiment 7.0: Baseline (offline-interaction-interval 50)
- Experiment 7.1: Changed offline-interaction-interval to 40
- Experiment 7.2: Changed offline-interaction-interval to 30
- Experiment 7.3: Changed offline-interaction-interval to 20

Chapter 5

Experimental Methodology

This chapter outlines the experimental methodology used to examine the dynamics of the opinion model discussed in preceding chapters. The experiments aim to examine the impact of several important factors on the model's behaviour, while guaranteeing that the results are statistically sound and representative.

5.1 Taking Comprehensive Runs

To systematically explore the impact of different parameters on the model's outcomes, we conducted a series of experiments where exactly one parameter was varied at a time. All other parameters were held constant at their baseline experiment values as specified later in Chapter 5.

For each experiment focusing on a specific parameter, we selected four different values within the parameter's defined range. This resulted in four sub-experiments per parameter. The selection of these values aimed to cover a meaningful spectrum of the parameter space to observe potential variations in the model's behaviour.

5.1.1 Simulation Runs

To account for the stochastic nature of the model and to ensure statistical reliability, each sub-experiment was replicated 99 times. Therefore, for each parameter under investigation, a total of $4 \times 99 = 396$ simulation runs were performed.

Each simulation was run for t in range 0 to 4999 time steps. At each time step t, the opinions of all alive agents were recorded. This extensive replication allows for the analysis of variability and the identification of representative behaviours within the stochastic model.

5.1.2 Data Recording

During each simulation run, the opinions of all agents alive at time step t were recorded. This resulted in a dataset containing 5000 time steps per run and with 99 runs per subexperiment. As a result, the total number of data points per sub-experiment amounted to approximately $5000 \times 99 = 495,000$ lines.

5.2 Representative Run Selection

Given the stochasticity of the model, it is essential to select a representative run for each sub-experiment that best reflects the typical behaviour of the system under the given parameter settings. To achieve this, we employed a method based on the mean opinion over time and the area under the curve (AUC) of this mean opinion.

5.2.1 Mean Opinion Calculation

For each simulation run, we calculated the mean opinion $\bar{o}_t$ of all alive agents at each time step t, where $t \in [0, 5000]$ such that $t \in \mathbb{W}$. The mean opinion at time t is given by:

$$\bar{o}_t = \frac{1}{N_t} \sum_{i=1}^{N_t} o_{i,t} \tag{5.1}$$

where:

- N_t is the number of alive agents at time step t.
- $o_{i,t}$ is the opinion of agent i at time step t.

5.2.2 Area Under the Curve Calculation

To quantify the overall behaviour of the mean opinion over time for each run, we calculated the area under the curve (AUC) of $\bar{o}_t$ from $t = 0$ to $t = 5000$. The AUC for run r is computed using the definite integral:

$$\text{AUC}_r = \int_0^{5000} \bar{o}_t \, dt \tag{5.2}$$

In practice, since the data is discrete at each time step, we approximated the integral using the trapezium rule:

$$\text{AUC}_r \approx \sum_{t=0}^{4999} \frac{\bar{o}_t + \bar{o}_{t+1}}{2} \Delta t \tag{5.3}$$

where $\Delta t = 1$ is the time step increment.

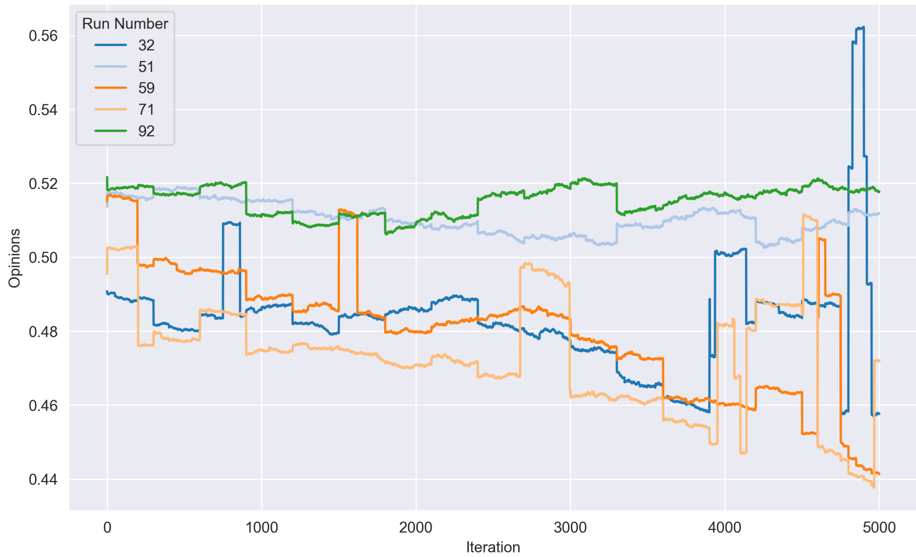

Figure 5.1: Mean opinion of all agents at each time step t for the 1st, 25th, 50th, 75th, and 100th percentile runs of the Baseline Experiment, ordered by AUC.

5.2.3 Run Selection Method

After computing the AUC for each of the 99 runs in a given sub-experiment, we sorted the runs based on their AUC values in ascending order. Let A_r denote the AUC of run r, and let the sorted list of runs be $(r_1, r_2, \ldots, r_{99})$ such that $A_{r_1} \leq A_{r_2} \leq \cdots \leq A_{r_{99}}$.

We then selected the median run as the representative run for the sub-experiment. Specifically, the representative run r_{med} corresponds to the run at the 50th percentile of the sorted list:

$$r_{\text{med}} = r_{50} \tag{5.4}$$

This strategy guarantees that the chosen run accurately reflects the standard behaviour seen in the sub-experiment, reducing the impact of outlier runs that may display unusual dynamics due to random fluctuations.

5.3 Visualising Opinion Distribution Over Time

To further evaluate the temporal dynamics of opinions in the typical runs, we constructed two-dimensional histograms (heatmaps) of the opinion distributions, equivalent to the methodology used by Deffuant et al. [2002] for the chosen representative run in each sub-experiment.

5.3.1 Data Processing

For the representative run r_{med}, we extracted the opinions of all alive agents at each time step t. This provided a set of opinion-time pairs $(o_{i,t}, t)$ for all agents i and time steps t.

5.3.2 Histogram Construction

We constructed a two-dimensional histogram by binning the opinion-time data into a grid. Let the opinion axis be divided into n_o bins of width Δo, and the time axis into n_t bins of width Δt. The density $D_{j,k}$ in each bin (j,k) is calculated as:

$$D_{j,k} = \frac{N_{j,k}}{N_{\text{total}}\Delta o \Delta t} \tag{5.5}$$

where:

- $N_{j,k}$ is the number of agents whose opinions and time steps fall into bin (j,k).
- N_{total} is the total number of opinion-time data points.
- Δo and Δt are the widths of the opinion and time bins, respectively.

5.3.3 Logarithmic Density Scaling

To enhance the visibility of regions with low agent densities, which might be obscured in linear scaling due to the wide range of densities, we applied logarithmic scaling to the density values. The logarithmic density $D'_{j,k}$ is given by:

$$D'_{j,k} = \log_{10}\left(D_{j,k} + \varepsilon\right) \tag{5.6}$$

where ε is a small constant (e.g., 10^{-4}) added to avoid taking the logarithm of zero.

5.3.4 Heatmap Visualisation

The heatmap provides a visual representation of how the distribution of opinions evolves over time:

- **X-axis (Time)**: Represents the time steps from $t = 0$ to $t = 4999$.
- **Y-axis (Opinion)**: Represents the opinion values from $o = 0$ to $o = 1$.
- **Shade Intensity**: Indicates the (logarithmic) density of agents holding a particular opinion at a given time step.

The use of a grey-scale colour map with transparency thresholds allowed us to visually emphasise areas of significant agent density while de-emphasising regions with negligible densities.

Chapter 6

Results

This chapter shows and explains the results we have obtained after implementing the model explained in chapter 3, setting up experiments 1, 6, and 7 outlined in chapter 4, and obtaining the results as per chapter 5. We discuss our findings and how the results can be interpreted, to then compare them to results from related literature in chapter 7.

For three chosen experiments, we compare the results of running the implemented model with the baseline configurations outlined in section 4.1, with the configurations for each of the respective experiments. The three experiments were selected due to their parameters playing a key role in the model implementation and due to their identified significance explored in related literature in chapter 2. The results of all other experiments can be seen in Appendix D.

6.1 Varying the Bubble Size

After running the first experiment described in section 4.2, the results are plotted using the process explained in chapter 5 to understand the impact of varying the bubble size parameter. As seen in Figure 6.2, when increasing the bubble size from 25 in increasing steps of 25, a significant shift in opinion distributions can be observed.

With each increase of this key parameter, the two polarised groups, set out at around zero or one at the beginning, start to move closer together towards a middle group around the 0.5 mark. This then suddenly changes for the last subexperiment with a more dispersed result of the agents when setting the bubble size to 100.

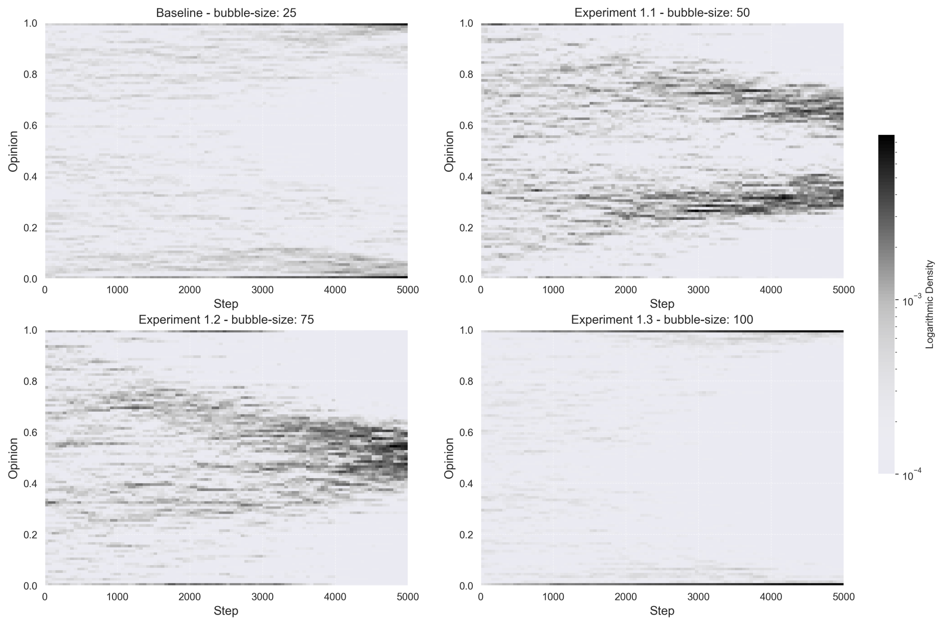

Figure 6.1: Experiment 1: Varying Bubble-Size

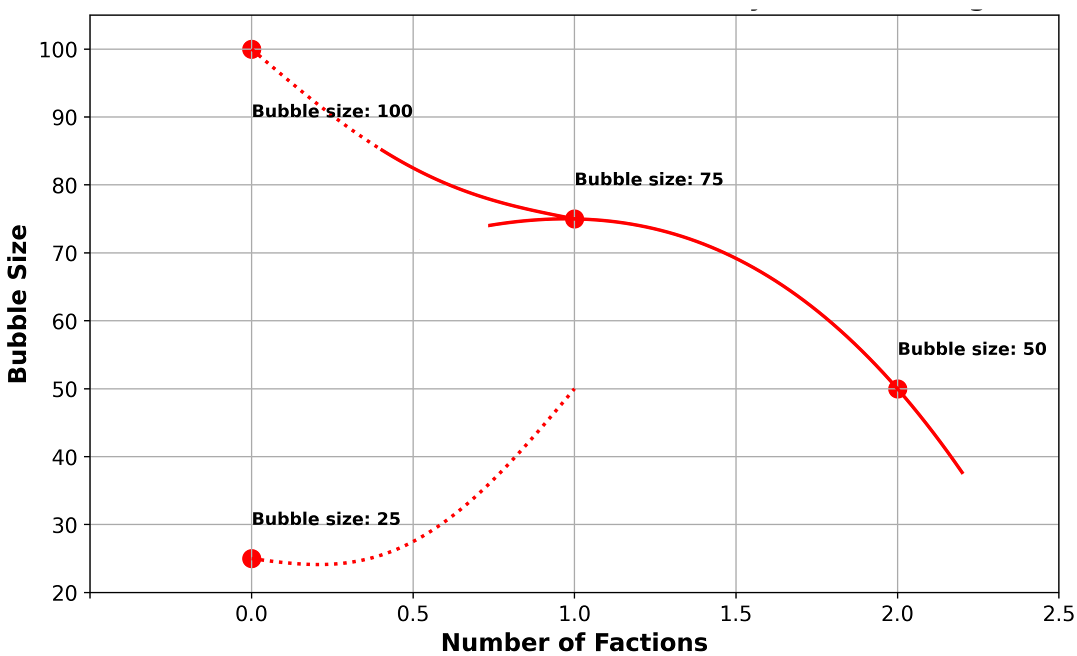

Figure 6.2: Experiment 1: Tipping point graph of non extremist factions

6.2 Changing the Online Agent Percentage

Another key parameter is the **online-agent-percentage** which was tested as part of the sixth experiment discussed in section 4.7. As seen in Figure 6.3, the baseline implementation starts with 90%, decreasing in steps of 20% with each experiment.

Here, the opinion distribution gets closer toward the middle-ground with each subexperiment, until four distinct major opinions can be observed to have formed by the online agents. This is inline with our related literature research in chapter 2, that polarised opinions tend to form stronger online than offline. When decreasing the online factor we actually observe a wider variety of opinions.

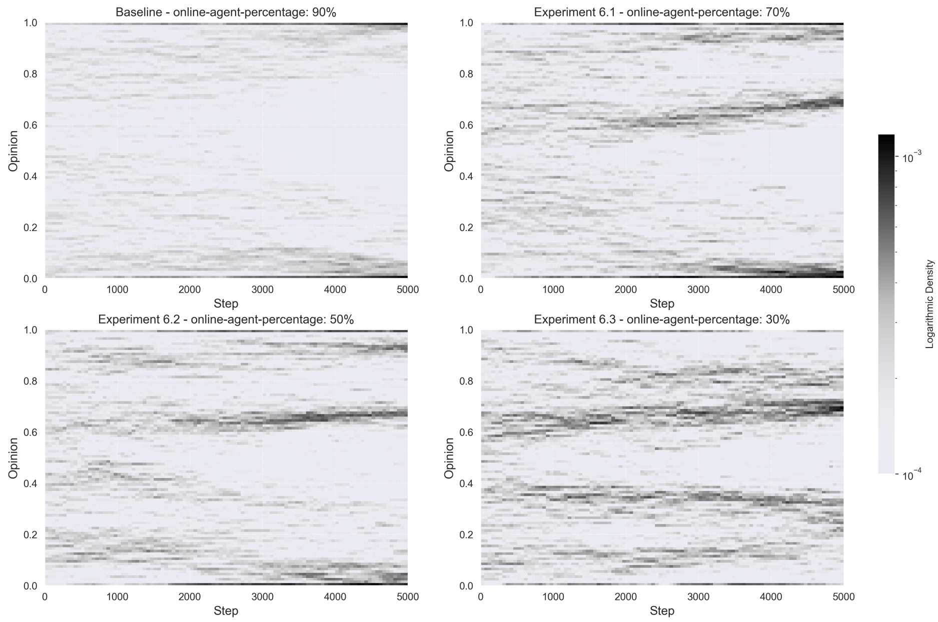

Figure 6.3: Experiment 6: Changing Online Agent Percentage

6.3 Varying the Offline Interaction Interval

As part of the seventh experiment outlined in section 4.8, the **offline-interaction-interval** parameter's results can be found in Figure 6.4. When changing the parameter from 50 to 20 in steps of 10, there is a trend of an opinion distribution shift from the polarised edges more toward the centre. This aligns with the related research of more offline interaction resulting in a larger variety of opinions amongst the population.

However, this reverts with the lowest setting of 20 ticks, in line with the previous results of an increased online interaction, where the agents interact more with the social media platforms and less in-person.

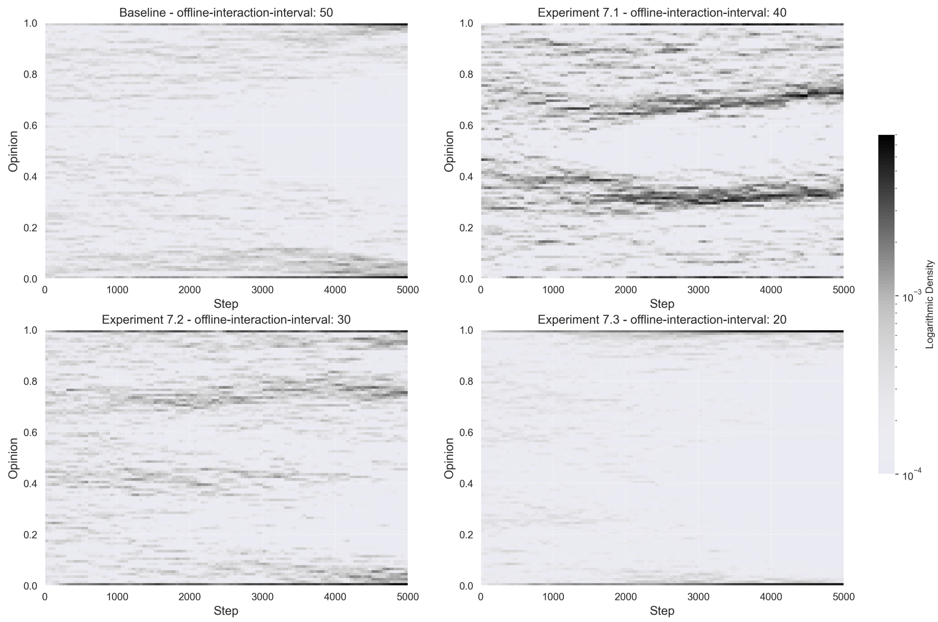

Figure 6.4: Experiment 7: Varying Offline Interaction Interval

6.4 Polarisation Metrics

After analysing the experiments results, we are also checking the impact on the polarisation metrics of spread, dispersion, coverage, and entropy described in section 2.4. We apply those metrics to each of the above experiments and subexperiments.

6.4.1 Spread

The observed polarisation spread using the median runs of the baseline compared with the first experiment can be found in Figure 6.5. Here, the spread stays consistently around the 1.0 mark with some small deviations of experiment 1.1 and experiment 1.2 in later time steps around 4500 ticks. The spread results for the other selected experiments can be found in subsection D.3.1.

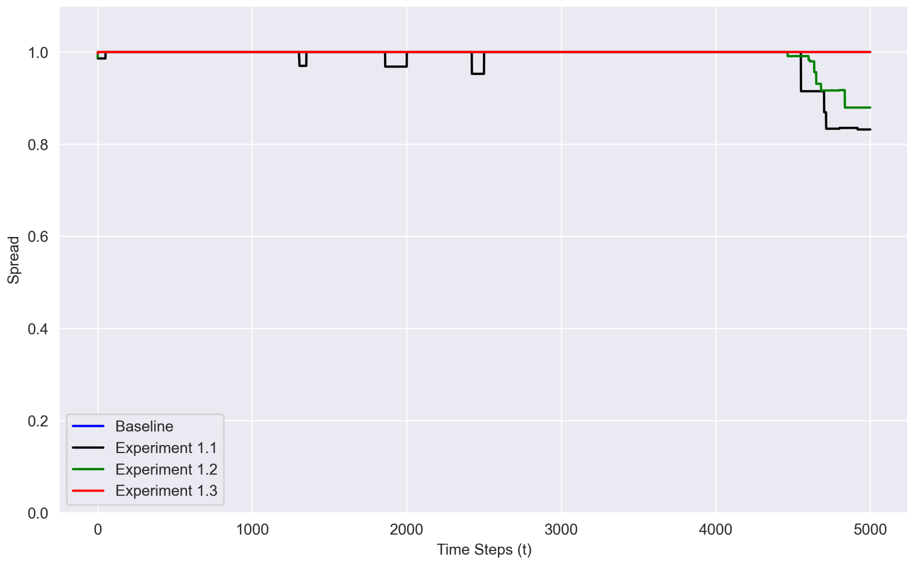

Figure 6.5: Polarisation Spread - Experiment 1

6.4.2 Dispersion

The polarisation dispersion results are shown in Figure 6.6 for the first experiment. The first experiment results in all four subexperiments branching out into their own patterns. The dispersions of the baseline and experiment 1.3 increase, while those of experiments 1.1 and 1.2 decrease. More dispersion results are displayed in subsection D.3.2.

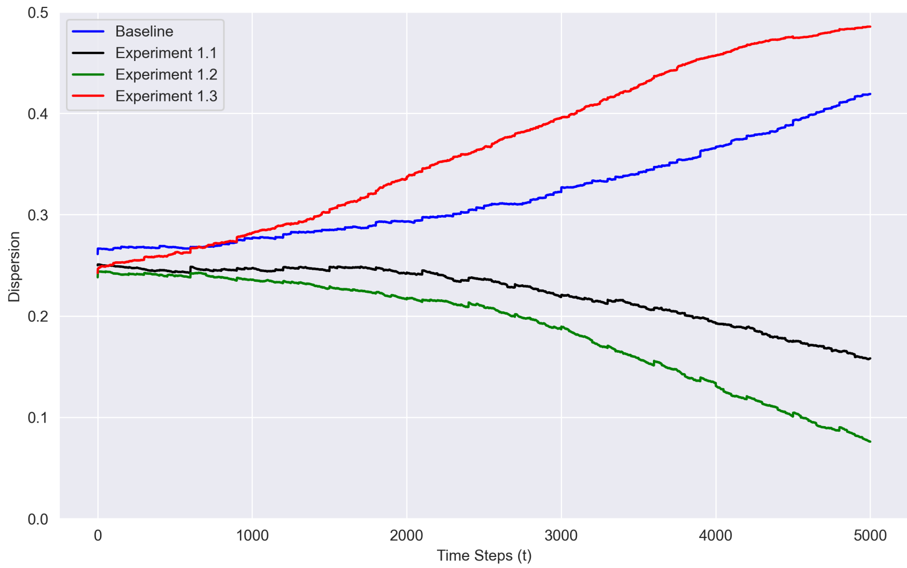

Figure 6.6: Polarisation Dispersion - Experiment 1

The sixth experiment's dispersion results are in Figure 6.7, where the baseline and experiments 6.1 and 6.2 all trend towards increased dispersion from around 0.25 to 0.35-0.42. Only subexperiment 6.3 has a strong decreasing trend resulting in about 0.12.

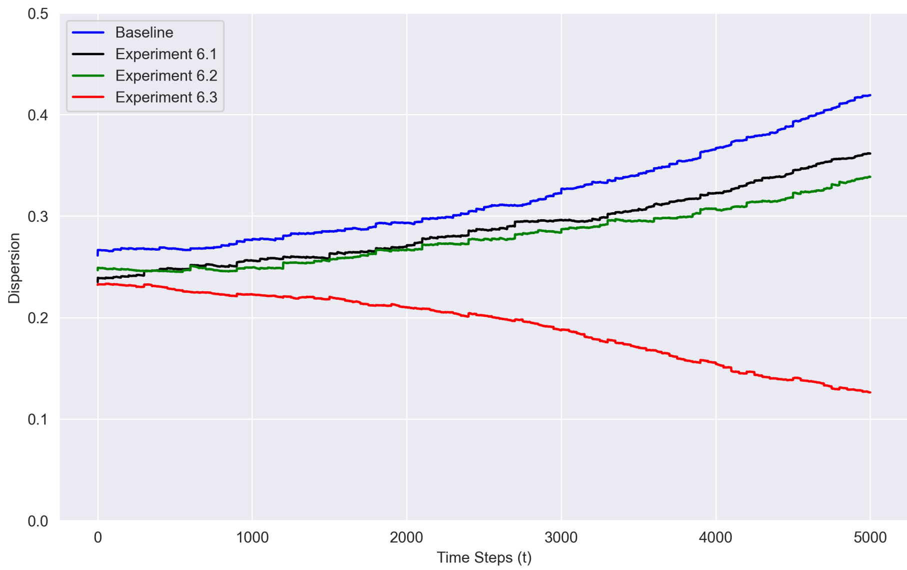

Figure 6.7: Polarisation Spread - Experiment 6

6.4.3 Coverage

The results of the polarisation coverage during the first experiment are in Figure 6.8. It can be observed that the baseline and all subexperiments except for 1.3 stay around the same level of 3-3.5. Only the 1.3 subexperiment shows a strong decreasing trend of detected coverage, almost reaching 1.0.

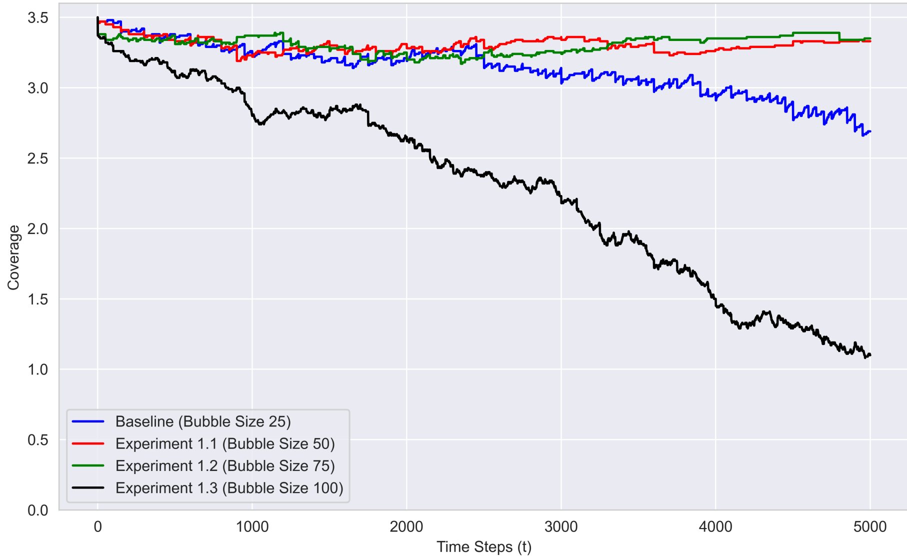

Figure 6.8: Polarisation Coverage - Experiment 1

6.4.4 Entropy

The polarisation entropy results during the seventh experiment are visualised in Figure 6.9, with more entropy plots available in subsection D.3.4. Here, we observe subexperiments 7.1 and 7.2 staying between 2.0 and 2.5, but the baseline and subexperiment 7.1 show a stronger decrease to 1.5 and about 0.8 respectively.

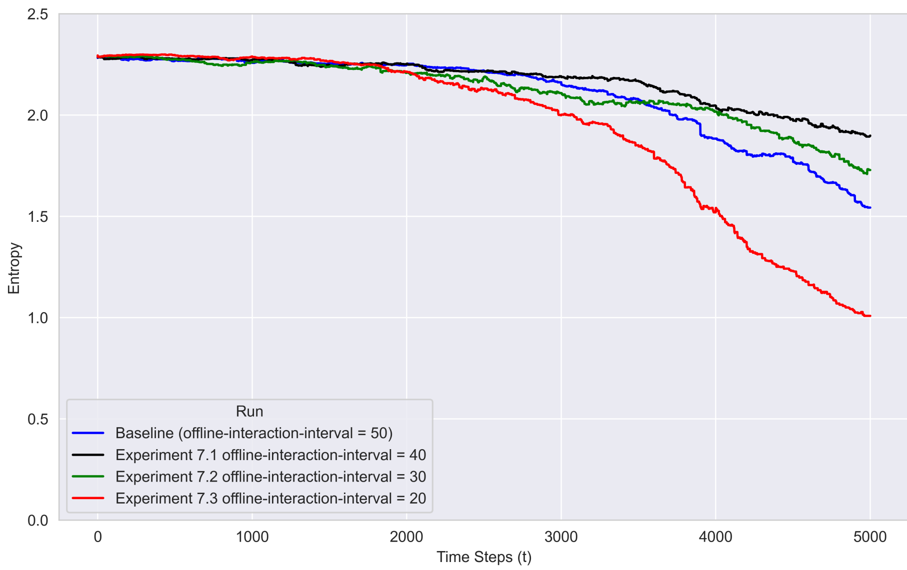

Figure 6.9: Polarisation Entropy - Experiment 7

6.5 Results Summary

Overall, using our set-out results, we have been able to observe a high impact of each of the three tested key parameters with each subexperiment. The bubble size parameter has a high impact, as was discussed earlier in chapter 3. Both the online agent percentage and offline interaction interval parameters similarly had the expected effect inline with the related literature findings explored earlier.

The polarisation metrics of spread, dispersion, coverage, and entropy earlier defined section 2.4, showed varying results by experiment and subexperiment. A common observation was a decreasing trend in all metrics toward later time steps of the median runs.

Chapter 7

Discussion

7.1 Results Comparison to Related Literature

Arora et al. calls for research going beyond the scope of merely focusing on whether the internet causes polarisation, which the model comes closer to by simulating an array of conditions, such as high personalisation versus diverse feeds, which providing insights into the complexities in the relation between social media and polarisation (Arora et al. [2022]).

The review (Arora et al. [2022]) also found that offline events play a key role in social media polarisation effects, such as the US election or controversial topics. While we have not taken into account real events, we have been able to simulate offline interaction by introducing the offline interaction interval parameter as part of the seventh experiment, as discussed in section 4.8.

Our results discussed in section 6.3 showed that lowering the **offline-interaction-interval** resulted in a more diverse range of opinions. However, the final sub-experiment with the lowest **offline-interaction-interval** showed a similar effect as the baseline with a heavily opposed opinion distribution. This aligns with the survey's findings of findings of both high and low offline interaction extremes, resulting in similar heavily polarised views, with a higher variety in-between the two extremes.

Similarly, our findings of the online agent percentage experiment explained in section 6.2 resulted in a higher variety of opinions with each decrease. This also aligns with the survey's findings of an increased number of online users resulting in higher polarisation and a less diverse range of opinions Arora et al. [2022].

The foundational model introduced earlier by Keijzer et al. [2024] found that the implemented model's bubble size has an inverse correlation with the opinion polarisation. It also found that the polarisation metrics of spread, dispersion, and coverage decreased with an increased bubble size. Our first experiment's results of varying the bubble size explained in section 4.2, partly align with these findings by having the high polarisation with the lowest bubble size setting. We also see the dispersion of the same experiment, discussed in subsection 6.4.2, decreasing with a high bubble size setting in subexperiment 1.2. However, these observed patters are not consistent across all bubble-size subexperiments.

7.2 Implementation Limitations

7.2.1 Complexities and multifaceted nature of real-life interactions

Although our model implements offline interactions, our approach may have been too simplistic, overlooking complexities and variabilities in real-life interactions. Bruns [2025] criticises oversimplified models of interaction. Bruns stresses the importance of the intricacies of overlaps between online and offline interactions. Our model largely assumes these are separate, and of equal value. Different interactions may influence agents to varying degrees, as the dynamics of offline and online interactions differ. In the real world, users likely engage in fewer offline interactions than online ones, potentially resulting in a more significant individual impact from offline interactions (Lieberman and Schroeder [2020]).

This could be alleviated by exerting a greater influence on agents in close geographical proximity. Nonetheless, this may still constitute a simplification, as online contacts differ in intensity - spanning from simple engagements like seeing an 'article' or 'post' to more profound, personal exchanges such as video calling. Future models could rectify these limitations by including a sophisticated weighting system for interactions, tailored to reflect the context and medium of communications so that they more accurately embody the multifaceted dynamics of contemporary communication.

7.2.2 Digital divides between geographical areas and generations

Our agent-based model, while effective in simulating the interplay between online and offline interactions in opinion dynamics, has several limitations related to its implementation that may impact the generalisability of results.

7.2.2.1 Uniform Internet Penetration and its Global Applicability

Firstly, the model assumes a uniform level of internet penetration across the agent population, reflective of Western or developed countries. This is achieved through the `online-agent-percentage` parameter in the code, which sets a static proportion of agents as online users upon initialisation. However, this does not take into account differences in access and usage of the internet by location, which can have a big impact on how polarisation manifests. Van Dijk [2019]. Regions with lower internet penetration may exhibit different polarisation outcomes, and our model does not capture these differences. This limitation affects the applicability of our findings to diverse global contexts.

7.2.2.2 Generational Differences in Technology Adoption

Secondly, although the model includes an ageing process where agents' group affiliation strengths increase and their opinions become more extreme over time (implemented in the `agent-ageing` procedure), it fails to consider generational differences in technology adoption. Agents retain their online or offline status throughout their lifespan, as determined at initialisation. This static assignment fails to reflect real-world scenarios where older generations often have lower adoption rates of digital platforms—not due to disengagement over time but because they never adopted them initially (Van Dijk [2019]). Consequently, our model may overlook important dynamics related to how generational shifts impact the proportion of online agents. This limitation is particularly relevant to our second research question (**RQ2**), which explores how altering the proportion of online agents affects opinion dynamics. Since the model does not simulate changes in online status over time or across generations, it cannot fully capture the effects of generational turnover on polarisation.

7.2.2.3 Geographical Dispersion and Its Impact on Offline Interactions

Lastly, the model does not simulate geographical dispersion or mobility of agents, which means it cannot account for the spatial clustering of opinions that might occur due to physical proximity or regional cultural differences. This limitation could affect the exploration of our third research question (**RQ3**), as the frequency and impact of offline interactions might vary significantly in a spatially heterogeneous environment (i.e. The agents could have been initialised in clusters of varying sizes rather than scattered randomly).

7.2.3 Tactics For Mitigating Polarisation

While our research utilises multiple experiments to understand polarisation, the model currently lacks methods for actively investigating mitigating strategies. For example, we did not execute algorithmic interventions that could reduce polarisation, such as dynamically altering the **bubble-size** parameter to counteract the filter bubble effect based on polarisation levels.

Arora et al. [2022] demonstrates the significance of algorithmic measures in decreasing polarisation. Subsequent versions of the model could include adaptive algorithms that modify interaction networks or impact weights according to real-time assessments of polarisation. This will not only render the model more useful for policymakers but additionally augment its utility in evaluating the efficacy of various mitigation techniques.

Moreover, extending the model to replicate the effects of heightened offline social cohesion could mitigate constraints associated with **RQ3**. Implementing community-building methods or enabling cross-group offline contacts may uncover strategies to mitigate online polarisation.

7.2.4 Lack of real-world datasets

7.2.4.1 Challenges in Incorporating Real-World Data

A significant drawback of our implementation is the absence of real-world datasets. Real world data may have improved the accuracy of our initial population. Our model fails to consider demographic-specific social media behaviours, and there is a lack of datasets regarding click-through rates, content sharing patterns, or interaction with polarised content.

7.2.4.2 Barriers to Accessing Relevant Datasets

Due to the limited scope of our research and the significant variability in available datasets suitable for the model, implementing all these features was not feasible. While we aimed to incorporate various real-world datasets, we encountered difficulties in accessing sufficient data across diverse topics. This challenge is compounded by the complexities of conducting multifaceted societal research, which often requires longitudinal studies. Such studies are particularly scarce given the relatively recent emergence of social media platforms Neves and Mead [2021].

7.2.4.3 Current Mitigations and Future Directions

Despite these limitations, the model incorporates data from empirical studies, such as the observed rise in affective polarisation, to align with real-world phenomena.

7.3 Experiments Limitations

The conducted experiments are limited by certain factors that have an impact on our results and therefore drawn conclusion. We outline these limitations so these can be addressed as part of future research on this topic, and to be kept in mind when reading through our results analysis.

Firstly, each experiment outlined in chapter 4 only focusses on changing one parameter at a time and observe its impact on the results. While this allows us to understand that individual variable better and link it to existing research, this excludes the possibility of analysing the impact of a combination of two or more factors together. This would be something that can be experimented with in future research but was not analysed as part of this project due to the selected research scope and computing constraints of the number of complicated experiments we can run.

Furthermore, we did not experiment with any of the alpha or gamma variables of the implemented model explained in chapter 3. We chose not to pursue this as there is no research evidence to link the results to, as it is our novel implementation. However, this is something that can be looked into as part of follow-up research.

The initial setup of the experiments used a uniform distribution of agents per opinion bucket and age range, instead of empirical survey or statistical data. This results in an initially unrealistic population dynamic. However, we set the initial group membership strength based on a normal distribution, which results in a more realistic population model in later stages of the model run. This can be further improved by setting the two mentioned variables based on real-life data in the future.

Additionally, each experiment's run was only run until reaching 5000 ticks. While this is enough to observe the general results trends of the observed variable, this can be expanded more in the future for more long-term insights. Similarly to the previous point, we chose to limit the runs at 5000 runs to focus on related research of short-term effects and due to computing constraints.

Finally, each experiment consisted of the baseline run compared to three sub-experiments. This could be expanded to more granular changes in the future resulting in a more robust overview of each parameter's impact. We chose to focus on a larger variety of experiments instead of more sub-experiments per experiment to have a better overview of each parameter. In the future, specific parameters can be inspected more granular by running more sub-experiments with smaller incremental setting changes.

Chapter 8

Conclusions

Our main contributions consist of researching related literature and identification of the problem the model is trying to solve in chapter 2. We have also implemented a NetLogo implementation from scratch based of a foundational model Keijzer et al. [2024] and described in detail in chapter 3. Further, we conducted robust experiments based on literature chapter 4. Afterwards, we found novel methods of evaluating of NetLogo experiments results described in chapter 5. Finally, we evaluated and plotting our results findings in chapter 6 and discussed our results compared to literature and listing limitations and areas of opportunity in chapter 7.

To conclude, further work and improvements include addressing the limitations of our implementation and conducted experiments outlined in chapter 7. This includes implementing the proposed model improvements and conducting further experiments where we have data or logic gaps. We could also incorporate real-world datasets and explore adaptive algorithms designed to mitigate polarisation in real-time. Further, the model could be expanded to include broader sociological and psychological influences.

We have identified thresholds and dynamics of social media polarisation and provided insights into balancing online and offline interactions for reducing polarisation. We highlighted the importance of sociological contexts in polarisation models. By incorporating an offline aspect to the Keijzer et al. [2024] model, we were able to imitate globalisation of offline interactions and their influence to a wider range of agents. Although polarisation is not exclusive to the online sphere, we have proven through our experiments that it is exacerbated by digitally exclusive means of communication.

The possible implications we have identified should encourage deeper sociological research to enhance model accuracy and realism. This could lead to informing policymakers on strategies for algorithmic interventions (e.g., promoting diverse feeds). We also call for more interdisciplinary collaboration on this crucial topic.

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Appendix A

ODD

The model description follows the ODD (Overview, Design concepts, Details) protocol for describing individual- and agent-based models (Grimm et al. 2006; 2010; Railsback and Grimm 2018).

A.1 Purpose and Patterns

The purpose of this agent-based model is to simulate the dynamics of opinion formation and polarisation within a population interacting both online and offline. The model's purpose is to understand how social interactions and individual agent attributes, such as age and group affiliation, influence the evolution of opinions over time. It incorporates key mechanisms such as filter bubbles, offline social interactions, and demographic processes including ageing, births, and deaths.

A.1.1 Patterns for Model Validation

To determine the usefulness of the model for its purpose, several patterns observed in real-world social systems are used as benchmarks:

1. **Opinion Distribution Evolution:** The model should reproduce characteristic patterns in opinion distributions, such as the emergence of distributions indicating polarisation, or convergence towards consensus under certain conditions.
2. **Polarisation Metrics Dynamics:** The model tracks quantitative measures of polarisation, including *Spread*, *Dispersion*, *Coverage*, and *Entropy*. These metrics should exhibit trends and fluctuations that align with empirical observations in studies of social polarisation.
3. **Group Influence Effects:** The model should capture how strong group affiliations and varying group strengths among agents influence the rate and extent of opinion polarisation or consensus formation.
4. **Impact of Filter Bubbles:** The simulation should demonstrate how online interactions confined within opinion bubbles (as determined by the **bubble-size**

parameter) lead to increased polarisation compared to scenarios with more diverse online interactions.

5. **Role of Offline Interactions:** The model should reflect how offline interactions, which are based on physical proximity and occur less frequently, contribute to opinion diversity and can counteract the effects of filter bubbles.

6. **Demographic Influence Patterns:** Patterns related to the impact of ageing, births, and deaths on opinion dynamics should be evident, such as generational shifts in opinions or changes in polarisation levels due to demographic turnover.

7. **Adaptation to Carrying Capacity:** The population size should stabilise around the carrying capacity, reflecting realistic constraints on population growth and resource availability.

We can see how well the model can actually show how opinions change and become more divided by comparing the simulation results to these patterns. The fact that the model's results fit these patterns shows that it can help us answer the research questions we gave it and learn more about how people form opinions in societies where people connect with each other both online and offline.

A.2 Entities, State Variables, and Scales

The model consists of agents interacting within a shared environment. The entities in the model are:

- **Agents (Turtles)**: Represent individuals in the population.
- **Environment**: A two-dimensional continuous space where agents reside and interact.

Agents

Each agent is characterised by the following state variables:

- **opinion**: A continuous variable ranging from 0 to 1, representing the agent's opinion on a certain topic.
- **group-strengths**: A list of real numbers between 0 and 1, representing the agent's strength of affiliation with each group in the model. It is important to note that groups are not treated as explicit entities in the model. Instead, they are tracked implicitly through this state variable. More information about the number of groups and group allocation will be described later in the Initialisation section.
- **age**: An integer representing the agent's age.
- **status**: A categorical variable indicating whether the agent is `online` or `offline`.
- **position**: The agent's physical location denoted by spatial coordinates (x, y) in the environment.

Environment

The environment is a two-dimensional continuous space with dimensions of 101 x 101 units. The space is continuous, allowing agents to occupy any point within it. The environment does not have additional state variables (no **patches-own** variables are declared). It serves as the medium in which agents move and partake in offline interactions.

Scales

Temporal Scale

Time is represented in discrete steps where each step is called a **tick**. Each **tick** represents a single unit of simulated time. The simulation runs iteratively, executing a set of procedures at each **tick** until a predefined maximum number of ticks (**max-ticks**) is reached.

Unit of Time/Interval	**Description**
Ticks (Time Steps)	The fundamental unit of time in the simulation. At each tick, a pair of online agents will interact with one another.
Ageing Interval (**ageing-interval**)	A specified number of ticks after which the ageing process occurs. During ageing, agents increase in age, and demographic events like births and deaths are processed.
Offline Interaction Interval (**offline-interaction-interval**)	The number of ticks defining how often offline interactions and agent movements occur. All agents physically move and a pair of agents which are close in proximity will interact with one another.

These intervals enable the model to replicate processes occurring at varying frequency. For example, online interactions occur frequently whereas ageing and offline interactions occur less often.

Spatial Scale

The spatial extent of the model is defined by the dimensions of the environment, which is a two-dimensional continuous space of size 101 x 101 units. The environment uses a wrap-around boundary that allows agents moving off one edge of the space to reappear on the opposite edge. This eliminates edge effects and simulates an unbounded environment.

Agents can move continuously in any direction and are not confined to discrete locations or patches.

Entity	State Variables
Agents	• **opinion**: Continuous value in [0, 1]. • **group-strengths**: List of group affiliation strengths in [0, 1]. • **age**: Integer representing the agent's age. • **status**: `online` or `offline`. • **position**: Spatial coordinates (x, y).
Environment	• **Dimensions**: Continuous space of size 101 x 101 units.

Table A.2: Summary of Entities and Their State Variables

Summary of Entities and State Variables

A.3 Process Overview and Scheduling

At each time-step (**tick**), the model executes its main procedure[1], which invokes the following processes in the specified order:

1. **Online Agent Interaction (Every Tick):** Agents engage in online interactions, influencing each other's opinions based on similarity and influence weights. The receiving agent's **opinion** will be updated here.

2. **Agent Ageing (Every ageing-interval Ticks):** Agents age, potentially die, and new agents may be born. All agents' **opinion** and **group-strengths** state variables are adjusted here. Newly born agents are initialised in the same manner to the process outlined in the Initialisation section, with the exception of their **opinion** state variable.

3. **Offline Agent Interaction and Movement (Every offline-interaction-interval Ticks):** Agents move in the environment and a pair of agents close in proximity interact with each other. The dynamically calculated **birth-rate** parameter may be reassigned here.

4. **Data Recording and Plotting (Every 100 Tick):** The model calculates polarisation measures including Spread, Dispersion, Coverage and Entropy. The time-series graphs on the interface are updated for analysis.

5. **Tick Advancement:** The simulation increments the tick counter and proceeds to the next time step.

The implementation of Steps 1, 2, and 3 will be explained in detail later in the submodels section. A structured diagram on the following page illustrates the temporal sequence and the invocation of subroutines.

[1]The main procedure serves as the entry point to the program's subroutines, analogous to the *go* subroutine in NetLogo. This is the highest-level routine in the model.

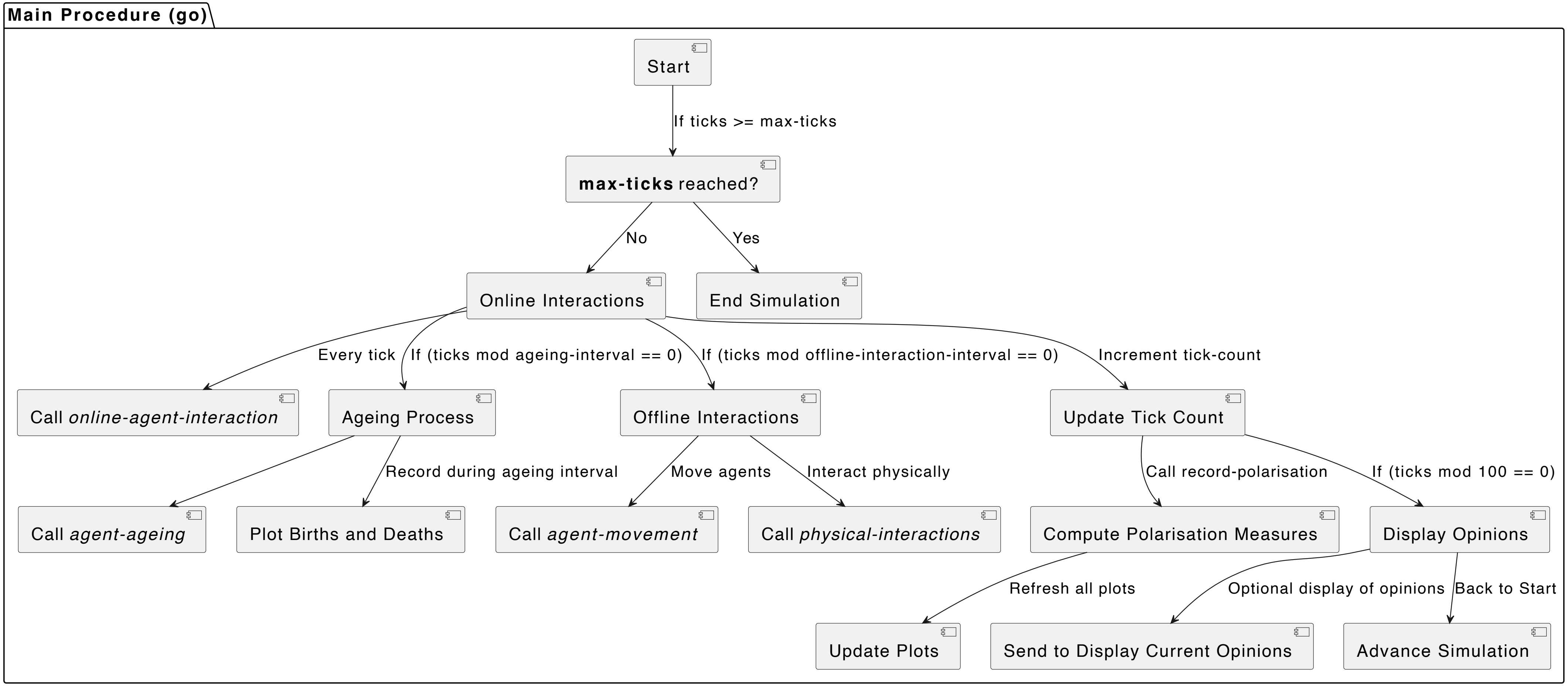

Figure A.1: A structured diagram illustrating the model's main procedure, representing the sequence of processes executed at each time step (tick). The diagram is read in a depth-first search manner, where each branch represents a subroutine invoked from the main procedure. Reading the diagram from left to right reveals the temporal structure and the flow of operations.

A.4 Design Concepts

A.4.1 Basic Principles

The model is based on individual-based theory, incorporating concepts from social influence, opinion dynamics, and population ecology (births, deaths and ageing.) It further extends these concepts by integrating the influences of group membership and dynamic shifts in opinion extremity. This model demonstrates system-level representations with individual-level interactions to explore emergent phenomena like polarisation dynamics and demographic transitions.

A.4.2 Emergence

Key emergent patterns such as opinion polarisation, group formation, and population dynamics are a direct result of local interactions and adaptive behaviours of agents. For example:

- **Opinion Metrics:** Spread, dispersion, entropy, and coverage based on individual opinion adjustments and influence rules.
- **Social Structures:** Emergent group membership similarities drive clustering and fragmentation, resulting in hoard mentality i.e. polarisation.
- **Population Changes:** Fluctuations in birth and death rates arise from adaptive demographic processes.

While some emergent trends, such as opinion truncation, are directly caused by explicit model rules, broader polarisation and demographic dynamics emerge independently from agent behaviours.

A.4.3 Adaptation

Agents adapt through:

- **Opinion Updates:** Adjusting their opinions $o_{i,t+1}$, based on interactions with other agents, weighted by group alignment and opinion similarity.
- **Movement:** Agents relocate randomly, adapting spatially to influence proximity interactions.
- **Group Strength Dynamics:** Group membership affiliation $s_{i,k,t}$ becomes stronger over time to reflect social reinforcement mechanisms.

These adaptations aim to recreate realistic social and demographic behaviours but do not explicitly optimise for 'success' metrics like fitness or utility. Importantly, our research methodology is designed to explore these dynamics impartially, rather than reaffirming pre-existing biases. This ensures that our findings contribute objectively to the understanding of complex social phenomena.

A.4.4 Objectives

Agents' overall objective is to align their opinions through social influence while staying within the bounded rationality interval [0, 1]. The objective is implicit, as humans tend to adjust opinions towards social conformity or group alignment. Regarding the larger demographic, the system seeks to maintain a more or less constant population size through dynamic birth rates.

A.4.5 Learning

Agents do not explicitly learn over time, but instead adapt reactively based on interactions. For example:

- Opinions are influenced by immediate social feedback rather than long-term learning.
- Group affiliation strength gradually increases as agents age, simulating social reinforcement without explicit memory or learning mechanisms.

A.4.6 Prediction

Agents in the model do not engage in explicit predictions; rather, their behaviours, such as opinion adjustments and group membership reinforcement, are directly influenced by the outcomes of immediate interactions. In contrast, demographic processes like birth rate adjustments operate on a more predictive basis, responding to current demographic trends, such as the proportion of young agents, to anticipate and manage future population pressures.

A.4.7 Sensing

Agents use sense in the following ways:

- **Opinion Differences:** They assess the difference between their own opinion o_i and that of an interaction partner o_j.
- **Group Membership Similarity:** Through $\delta_{e,ij}$, agents detect alignment with others based on shared group memberships.
- **Local Proximity:** Offline interactions depend on sensing neighbours within a radius of $R_{\text{interaction}}$. This sensing is modelled explicitly, relying on local or interaction-based information rather than global awareness.

A.4.8 Interaction

Interactions are of two types:

- **Online Interactions:** Agents connect based on opinion similarity (filter bubble effects).

- **Offline Interactions:** Proximity-based interactions where agents interact with randomly selected nearby peers. Interactions influence opinions through weight adjustments (ω_{ijt}), incorporating group similarity and opinion differences.

A.4.9 Stochasticity

Stochastic elements include:

- **Agent Movement:** Randomised direction vectors $\mathbf{u}_i$.
- **Opinion Inheritance:** Newborn agents inherit opinions with added randomness to prevent artificial clustering.
- **Mortality and Births:** Probabilistic events like death (p_{death}) and dynamic birth rates introduce variability.

These random elements allow the model to account for uncertainty in social and demographic behaviours, making the model more realistic.

A.4.10 Collectives

Agents belong to collectives implicitly defined by group membership traits $s_{i,k}$. These collectives influence individual susceptibility to opinion change through α_{total} and $\delta_{e,ij}$. While collectives are caused by shared group membership, they shape broader dynamics like opinion clustering and polarisation.

A.4.11 Observation

Data collected includes:

- **Opinion Metrics:** Spread, dispersion, entropy, and coverage, sampled each time-step to track polarisation dynamics.
- **Demographic Metrics:** Population size, birth/death rates, age distribution, and group memberships.

A.5 Initialisation

At time $t = 0$, the model initialises the simulation environment and the agent population based on the baseline experiment parameters (section 4.1). The initialisation process involves setting up the agents with their respective state variables and preparing the global variables required for the simulation run.

A.5.1 Environment Initialisation

The environment is a two-dimensional continuous space of 101 by 101 units. It utilises wrap-around boundary conditions, enabling agents to traverse the boundaries of the space without interruption caused by blockages.

A.5.2 Agent Initialisation

A total of 350 agents are created at the start of the simulation. Each agent represents an individual in the population and is initialised with the following state variables:

- **opinion**: Assigned a random value uniformly distributed between 0 and 1.
- **age**: Assigned a random integer value between 0 and **max-age** (100), representing the agent's initial age.
- **group-strengths**: Initially declared as a list of strengths for each of the **num-groups** (6) groups in the simulation.
  - If **multiple-group-membership** is enabled (which is the case in the baseline experiment parameters set), each agent belongs to a number of groups sampled from a normal distribution with mean **avg-num-groups-per-agent** (2) and standard deviation **sd-num-groups-per-agent** (1).
  - The actual number of groups per agent is bounded between 1 and **num-groups** (6).
  - For each group an agent belongs to, the group strength is assigned a random value uniformly distributed between 0 and 1 (since **binary-group-membership** is off). The strengths for groups the agent does not belong to are set to 0.
- **status**: Assigned as either `online` or `offline` based on the **online-agent-percentage** parameter (90% online).
- **position**: Placed at a random location within the environment.

Global Variable Initialisation

The following global variables are initialised:

- **tick-count**: Set to 0.
- **spread-list**, **dispersion-list**, **coverage-list**, **entropy-list**: Initialised as empty lists to record polarisation measures over time.
- **spread**, **dispersion**, **coverage**, **entropy**: Set to 0, representing the initial polarisation metrics.
- **total-births**, **total-deaths**: Set to 0, tracking the cumulative number of births and deaths.
- **births-this-ageing**, **deaths-this-ageing**: Set to 0, tracking births and deaths within the current ageing interval.

A.5.3 Initialisation Consistency

The initialisation process is stochastic due to the random assignment of opinions, ages, group memberships, and positions. Therefore, each simulation run can start with a different initial state, even with the same baseline parameters. This stochasticity enables the model to encompass many initial conditions. It therefore increases the variability of the simulation outcomes.

A.5.3.1 Data Sources

The initial values for the agents' state variables are selected to represent a generic population in the absence of specific empirical evidence. Agent age is assigned using a uniform distribution for the initial population. Over several ageing intervals, the anticipated population age distribution will emerge. The number of groups to which an individual may belong and their initial group strength affiliations are designed to reflect those of a typical population.

A.5.3.2 Varying The Parameter Values

For details on the range of appropriate values for the parameters used in initialisation, please refer to table: A.6.

With that in mind, we include several checks to ensure that the input parameters are set within well-reasoned and operational bounds. These checks are crucial for preventing runtime errors and ensuring that the simulation behaves as expected. It is important to note that in some modelling applications, such as NetLogo, it is not possible to constrain parameter sliders based on the current values of other parameter sliders. This limitation necessitates explicit runtime checks to maintain the integrity and logical consistency of parameter configurations. Below are the specific conditions checked:

- **Group Membership Constraints:**
  - *Average Number of Groups per Agent:* Ensures that the average number of groups each agent belongs to does not exceed the total number of available groups. This check prevents a configuration error where agents are expected to belong to more groups than actually exist.

    ```
    IF avg-num-groups-per-agent > num-groups  THEN
        SEND "Error: avg-num-groups-per-agent
        cannot be greater than num-groups." TO
        DISPLAY
        END PROCESS
    END IF
    ```

  - *Minimum Group Membership:* Ensures that the average number of groups per agent is at least 1, which guarantees that every agent is part of at least one group.

    ```
    IF avg-num-groups-per-agent < 1 THEN
        SEND "Error: avg-num-groups-per-agent
        must be at least 1." TO DISPLAY
        END PROCESS
    END IF
    ```

- **Group Strength Distribution:**
  - *Logical Upper Bound for Standard Deviation:* The standard deviation should not exceed half the total number of groups to prevent impractical variation.

```
IF sd-num-groups-per-agent > (num-groups / 2) THEN
    SEND "Error: sd-num-groups-per-agent
    must be less than or equal to num-groups divided
    by 2." TO DISPLAY
    END PROCESS
END IF
```

- **Population Capacity:**
  - Ensures that the environment's carrying capacity is never set below the initial number of agents. This check is crucial to avoid overpopulation relative to the designated environment capacity at the start of the simulation.

```
IF carrying-capacity < num-agents THEN
    SEND "Error: carrying-capacity must be
    greater than or equal to num-agents." TO DISPLAY
    END PROCESS
END IF
```

These checks are done to make sure that the simulation settings are correct and that they make sense. It also ensures that all of the initial conditions can work in the modelled scenario.

A.6 Input data

Not applicable.

A.7 Submodels

This section provides detailed descriptions of the submodels implemented in the simulation, including the mathematical formulations and procedures. The following submodels are elaborated upon:

1. Online Agent Interaction
2. Agent Ageing
3. Offline Agent Interaction and Movement

A.7.1 Online Agent Interaction

At each tick, a pair of online agents interact with each other, influencing their opinions. The procedure for online agent interaction involves the following steps:

1. **Receiver Selection:** A random online agent (ie. an agent with state variable **status** set to 'Online') i is selected as the receiver.
2. **Bubble Formation:** A bubble of agents is formed based on opinion similarity. The size of the bubble is determined by the parameter **bubble-size**, representing a percentage of the total population. The agents within the bubble are those with opinions most similar to the receiver.
3. **Sender Selection:** A random agent j is selected from the bubble to interact with the receiver.

   The pseudocode for steps 1 through 3 is as follows:

```
// Selects a random receiver
SET receiver TO one-of (agents)

// Determines bubble size (as a number of agents)
SET bubble_size_proportion TO bubble_size / 100
SET num_in_bubble TO max(1, round(bubble_size_proportion *
(count(agents) - 1)))

Excludes the receiver from the list of potential senders
SET other_agents TO [agents where self != receiver]

FOR EACH agent IN other_agents DO
    SET opinion_difference TO ABS(opinion - opinion of receiver)
END FOR

// Sorts other agents by opinion difference
SET sorted_agents TO SORT(other_agents BY opinion_difference)

// Selects the bubble (the closest agents in opinion)
SET bubble_agents TO SUBLIST(sorted_agents, 0, num_in_bubble)

// Picks a random sender from the bubble
SET sender TO one-of bubble_agents
```

4. **Opinion Difference:** The opinion difference between the sender and receiver is calculated as:

$$\delta = O_j - O_i \tag{A.1}$$

   where O_i and O_j are the opinions of the receiver and sender, respectively.

5. **Group Similarity:** The group similarity $\delta_{e_{ij}}$ between the receiver and sender is computed using the cosine similarity of their group strength vectors:

$$\delta_{e_{ij}} = \frac{1}{n}\sum_{k=1}^{n} s_{ik}s_{jk} \tag{A.2}$$

where s_{ik} and s_{jk} are the group affiliation strengths of agent i and j in group k, and n is the total number of groups.

6. **Influence Weight:** The influence weight w_{ijt} is calculated as:

$$w_{ijt} = 1 - \gamma_0|\delta| + \gamma_1(1 - \delta_{e_{ij}})|\delta| \tag{A.3}$$

where γ_0 and γ_1 are parameters controlling the influence of opinion difference and group similarity, respectively. The influence weight is truncated to the range $[-1, 1]$.

7. **Adjustment Factor:** The adjustment factor α is computed as:

$$\alpha = \alpha_0 + \alpha_1\delta_{e_{ij}} + \alpha_2 s_i \tag{A.4}$$

where α_0, α_1, and α_2 are parameters, and s_i is the mean group strength of the receiver.

8. **Opinion Update:** The receiver's opinion is updated based on the influence from the sender:

$$O_i \leftarrow O_i + \alpha w_{ijt}\delta \tag{A.5}$$

The opinion is constrained to the range $[0, 1]$.

The pseudocode for steps 4 through 8 is as follows:

```
// Computes opinion difference between sender and receiver
SET delta TO sender['opinion'] - receiver['opinion']
SET delta_abs TO ABS(delta)

// Computes group similarity delta_eij
SET sum TO 0
FOR counter FROM 1 TO num-agents DO
     SET sum TO sum + (receiver[group_strengths[counter]] *
     sender[group_strengths[counter]])
END FOR

SET delta_eij TO sum / num-agents
SET one_minus_delta_eij TO 1 - delta_eij

// Calculates influence weight
SET w_ijt TO 1 - gamma0 * delta_abs + gamma1
* one_minus_delta_eij * delta_abs

// Ensures w_ijt is between -1 and 1
```

```
IF w_ijt > 1 THEN
    SET w_ijt TO 1
ELSE IF w_ijt < -1 THEN
    SET w_ijt TO -1
END IF

// Computes adjustment factor
SET s_i TO AVE(group-strengths OF receiver)
SET total_alpha TO alpha0 + alpha1 * delta_eij + alpha2 * s_i

// Updates receiver's opinion
SET delta_opinion TO total_alpha * w_ijt * delta
SET receiver['opinion'] TO receiver['opinion'] + delta_opinion

// Ensures opinion is within the range [0, 1]
IF receiver['opinion'] > 1 THEN
    SET opinion OF receiver TO 1
ELSE IF receiver['opinion'] < 0 THEN
    SET opinion OF receiver TO 0
END IF
```

A.7.1.1 Parameters Used in Online Interaction

In the above we use mathematical notation to denote some parameter names as symbols. The table on the following page shows the symbol, the parameter name, and a description of the parameters involved.

Symbol	Parameter	Description
NA	**bubble-size**	The maximum number of agents that are considered within an agent's "bubble" during online interactions. The bubble size determines how many agents an agent can interact with based on proximity of opinion.
n	**num-groups**	The total number of distinct groups in the simulation. Agents can belong to one or more of these groups, depending on the model configuration.
α_0	**alpha0**	Baseline adjustment factor influencing the strength of opinion updates during interactions, irrespective of group similarity or individual differences.
α_1	**alpha1**	Modifies the adjustment factor based on the group similarity between interacting agents, enhancing the influence on opinion update.
γ_0	**gamma0**	Serves as a factor for controlling the influence of absolute differences in opinion, lessening the weight of influence as dissimilarity increases.
γ_1	**gamma1**	Increases the impact weight when there is less similarity among group members, making the influence effects stronger when there is more diversity among group members. It is crucial to observe that when γ_1 is negative, the effects are reversed.
α_2	**alpha2**	Affects the adjustment factor based on the mean group strength of the receiving agent, reflecting the agent's embeddedness in their groups on their susceptibility to influence.

Table A.3: Parameters and Variables for Online Agent Interaction

A.7.2 Agent Ageing

Every **ageing-interval** ticks, agents undergo ageing, which includes increasing age, adjusting group strengths and opinions, handling deaths, and processing births.

A.7.2.1 Age Increment and Deaths

1. **Age Increment:** Each agent increments its age:
$$age \leftarrow age + 1 \tag{A.6}$$
2. **Natural Death:** Agents reaching the maximum age as defined by the **max-age** parameter die automatically.
3. **Age-Dependent Death Probability:** Agents have an increased probability of dying as they age:
$$P_{\text{death}} = base\_death\_rate + \left(\frac{age}{max\_age}\right) \times age\_death\_factor \tag{A.7}$$
If a random number between 0 and 1 is less than P_{death}, the agent dies.

A.7.2.2 Group Strength Adjustment

Agents adjust their group strengths to move towards full strength (1):

$$s \leftarrow s + (1 - s) \times group\_strength\_increase \tag{A.8}$$

Here, s represents an individual component of the group membership state variable vector **group-strengths** associated with a given agent.

Each group strength s is constrained to the range $[0, 1]$.

A.7.2.3 Opinion Extremity Adjustment

Agents' opinions adjust towards the extremes (0 or 1):

$$O_i \leftarrow \begin{cases} O_i + (1 - O_i) \times opinion\_extremity\_increase, & \text{if } O_i > 0.5 \\ O_i - O_i \times opinion\_extremity\_increase, & \text{if } O_i \leq 0.5 \end{cases} \tag{A.9}$$

Opinions are constrained to $[0, 1]$.

A.7.2.4 Births

New agents are born based on the current population and carrying capacity:

$$births = \text{round}\,(birth\_rate \times (carrying\_capacity - current\_population)) \tag{A.10}$$

Newborn agents are initialised similarly to the initial population, except their opinions are inherited from a random agent with slight variation from existing agents.

A.7.2.5 Dynamic Birth Rate Adjustment

The birth rate is an auxiliary variable that adjusts dynamically based on the proportion of young agents out of the entire population:

1. **Compute Young Agent Ratio:**

$$young\_ratio = \frac{\text{number of agents with } age < 10}{\text{total number of agents}} \tag{A.11}$$

2. **Adjust Birth Rate:** If $young\_ratio > threshold$, decrease birth rate gradually to 0.1; if $young\_ratio < threshold$, increase birth rate gradually to 0.2.

The following pseudocode outlines the method we use to gradually increase or decrease **birth-rate**.

```
PROCEDURE adjust-birth-rate():

  DECLARE young_agents INITIALLY number of agents under 10 years old
  DECLARE total INITIALLY number of agents
  DECLARE young_ratio INITIALLY 0
  DECLARE excess_ratio INITIALLY 0
  DECLARE deficit_ratio INITIALLY 0

  // The values are predefined. We do not recommend changing them.
  DECLARE threshold = 0.2
  DECLARE lower_birth_rate = 0.1
  DECLARE normal_birth_rate = 0.2

  // The number of agents should be a positive integer at all times.
  // When no agents are present, we raise an error.
  IF total > 0 THEN
     SET young_ratio TO young_agents / total
  ELSE
     RAISE ERROR
  END IF

  IF young_ratio > threshold THEN
     SET excess_ratio TO young_ratio - threshold
     SET birth_rate TO max(lower_birth_rate,
     normal_birth_rate - excess_ratio)
  ELSE
     SET deficit_ratio TO threshold - young_ratio
     SET birth_rate TO min(normal_birth_rate,
     lower_birth_rate + deficit_ratio)
  END IF

END PROCEDURE
```

A.7.2.6 Carrying Capacity, Current Population and Dynamic Birth Rate

At each **tick** that is a multiple of **ageing-interval**, we count the number of current living agents. If this agent headcount is lower than the value provided by the **carrying-capacity** parameter, the model computes the available capacity, defined as the difference between the carrying capacity and the number of alive agents.

The available capacity is subsequently multiplied by the birth rate to assess the prospective addition of additional agents. The outcome is rounded to the nearest integer to obtain the precise number of births. If the current population meets or surpasses the carrying capacity, no new agents are produced. This approach guarantees that population growth is adaptively regulated in accordance with the environment's capacity.

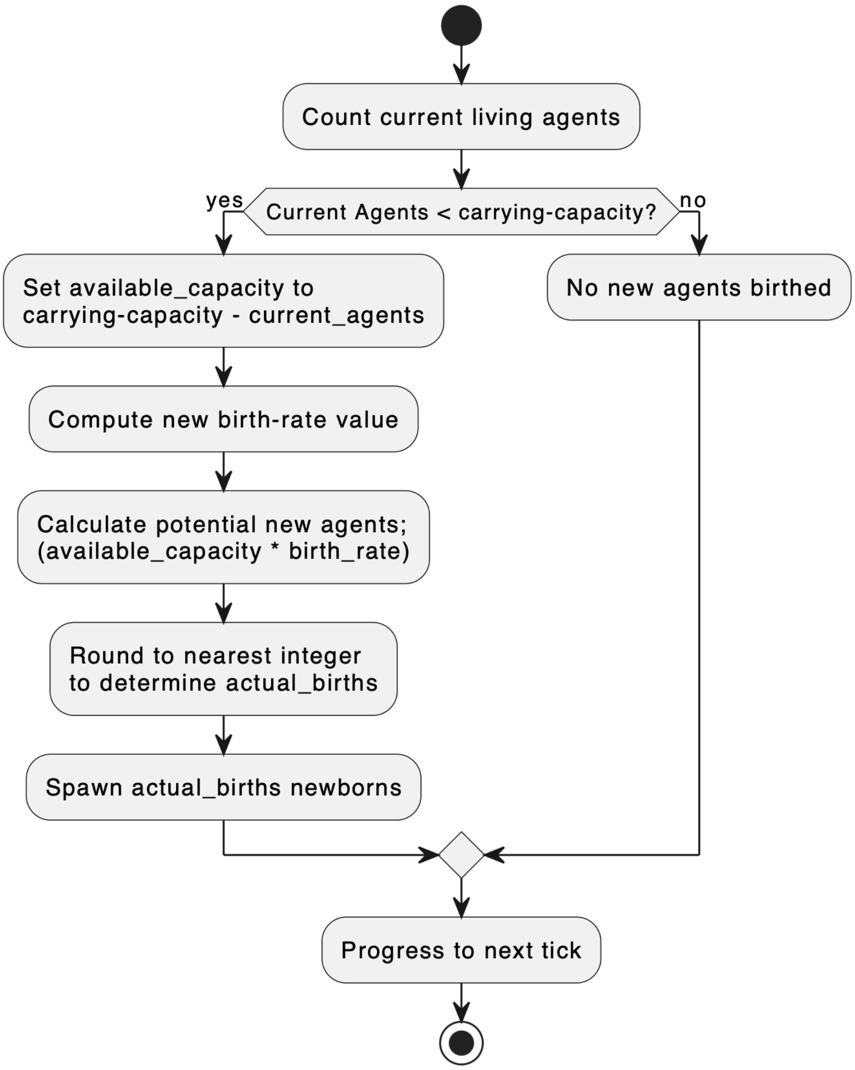

Figure A.2: High-level flowchart for when $t \mod T_{\text{ageing}} = 0$ at the agent birth subroutine. Here we are illustrating that the number of births is based on the dynamic birth rate, carrying capacity, and current population.

A.7.2.7 Agent Ageing Parameters

Parameter	Description
ageing-interval	The number of ticks between ageing events. During ageing, agents' ages increase, and demographic events such as births and deaths are processed.
max-age	The maximum age an agent can reach before it dies. Agents reaching this age are automatically removed from the population.
base-death-rate	The baseline probability of an agent dying at each tick. This rate is constant across all agents regardless of age.
age-death-factor	A factor that increases the probability of death as agents age, simulating higher mortality rates among older agents.
group-strength-increase	The rate at which agents' group strengths adjust towards 0 or 1 during each ageing event. This models the tendency of group affiliations to become more pronounced over time.
opinion-extremity-increase	The rate at which agents' opinions move closer to the extremes (0 or 1) during each ageing event, simulating the process of opinions becoming more polarized over time.
carrying-capacity	The maximum number of agents that the environment can sustain. When the population approaches this limit, the number of newborns dynamically adjusts to prevent overcrowding.

Table A.4: Parameters for Agent Ageing

A.7.3 Offline Agent Interaction and Movement

Every **offline-interaction-interval** ticks, agents move and may interact with nearby agents. All agent will move instantaneously. The receiving and sending agents are picked after all agents have moved (i.e. The agents do not move during the interaction)

A.7.3.1 Agent Movement

Agents move in random directions:

1. All agents turn in a random direction between 0 and 360 degrees.
2. They then move forward by a distance specified by the **movement-distance** parameter.

A.7.3.2 Offline Agent Interaction

1. One receiver is randomly chosen from the pool of agents.

2. An agent's status can be either `online` or `offline`. Although online agents predominantly engage in opinion-based interactions, they are equally likely to partake in offline interactions when compared to offline agents.

3. A random sending agent is picked from within the receiving agent's **offline-interaction-radius**.

4. The receiver and sender then interact using the same protocol as in online agent interaction, starting from step 4 of A.7.1 onwards.

A.7.3.3 Note on Interaction Equations

The offline agent interaction uses the same equations as the online agent interaction (see Section 3.1) for calculating opinion difference, group similarity, influence weight, adjustment factor, and opinion update. The primary difference lies in the selection criteria for interacting agents—offline interactions are based on physical proximity rather than opinion similarity.

A.7.3.4 Offline Interaction Parameters

The table on the following page describes each parameter involved in the Offline Interaction submodel.

Parameter	Description
offline-ageing-interval	The number of ticks between offline interactions and ageing events. Every interval, agents move and interact physically with others in the environment.
movement-distance	The distance an agent moves during each tick when performing offline movements. This distance is in units of the environment.
interaction-radius	The radius within which agents can interact with each other during offline interactions. Only agents within this radius will be able to engage in physical interactions. Again, this is measured in arbitrary units of the environment.
alpha0	Baseline adjustment factor influencing the strength of opinion updates during interactions, irrespective of group similarity or individual differences.
alpha1	Modifies the adjustment factor based on the group similarity between interacting agents, enhancing the influence on opinion update.
gamma0	Serves as a factor for controlling the influence of absolute differences in opinion, lessening the weight of influence as dissimilarity increases.
gamma1	Increases the impact weight when there is less similarity among group members, making the influence effects stronger when there is more diversity among group members. It is crucial to observe that when γ_1 is negative, the effects are reversed.
alpha2	Affects the adjustment factor based on the mean group strength of the receiving agent, reflecting the agent's embeddedness in their groups on their susceptibility to influence.

Table A.5: Parameters for Offline Interactions and Agent Movement

Parameter	Min Value	Max Value	Increment
num-agent	10	1000	1
carrying-capacity	11	2000	1
max-ticks	100	100,000	10
bubble-size	1	100	1
num-groups	2	10	1
multiple-group-membership?	ON or OFF		
binary-group-membership?	ON or OFF		
avg-num-groups-per-agents	1	10	1
sd-num-groups-per-agents	1	5	1
ageing-interval	50	1000	50
max-age	50	100	1
base-death-rate	0	0.0005	0.0001
age-death-factor	0	0.1	0.01
group-strength-increase	0	0.15	0.01
opinion-extremity-increase	0	0.1	0.01
offline-interaction-interval	0	500	1
online-agent-percentage	0	100	1
interaction-radius	0	10	1
movement-distance	0	10	0.1
alpha0	0	1	0.01
alpha1	0	-1	0.01
alpha2	0	1	0.1
gamma0	0	5	0.01
gamma1	-5	5	0.01

Table A.6: Recommended Parameter Ranges

Appendix B

Calibration of Population Dynamic Variables

Here, we detail the calibration process for the predefined (hardcoded) variables used in the model to ensure that the population size remains approximately constant as the number of time steps approaches infinity. The key parameters adjusted are:

- **Threshold for Young Ratio** (`threshold`): Set to 0.2 (20%).
- **Lower Birth Rate** (`lower_birth_rate`): Set to 0.1.
- **Normal Birth Rate** (`normal_birth_rate`): Set to 0.2.
- **Birth Rate when No Agents Exist**: Set to 0.25.

B.1 Calibration Objective

The primary objective of calibrating these parameters was to achieve a stable population size over the course of the simulation. Specifically, we aimed for the population size to remain close to the initial number of agents (`num-agents`) as time progresses towards infinity. This steadiness is important for studying how opinions change over time without large changes in the population getting in the way.

B.2 Calibration Process

The calibration involved iterative simulations and adjustments to the parameters to balance the birth and death processes in the model. The steps taken were as follows:

1. **Initial Parameter Estimation**: We began by experimenting with a range of values that seemed reasonable for the birth rates and the young ratio threshold.
2. **Simulation Runs**: Multiple simulations were executed using these initial values and we watched the population dynamics over an extended number of ticks (time steps).

3. **Adjustment of Birth Rates**:
    - If the population showed a consistent increasing trend, we reduced the **normal_birth_rate** and/or increased the **base_death_rate**.
    - If the population was declining, we increased the **normal_birth_rate** and/or decreased the **base_death_rate**.
4. **Fine-Tuning the Threshold**: The **threshold** variable, representing the proportion of young agents (age less than 10), was adjusted to control when and how the birth rate adapts during the simulation.
5. **Final Value Selection**: After several iterations, we settled on the values that resulted in a stable population size with minimal fluctuations around the initial number of agents.

B.3 Rationale Behind the Values

This section explains the rationale behind the choice of the hardcoded values used in the simulation to manage the agent population dynamics effectively.

B.3.1 Threshold for Young Agent Proportion (θ)

- **Threshold ($\theta = 0.2$)**: The threshold is set at 20%. This value is chosen because if the proportion of young agents (y) falls below this level, the birth rate (b) is boosted upwards to rapidly replenish the population. Conversely, if y exceeds this threshold, b drops down to prevent overpopulation. Together, we find that this maintains a balanced demographic.

B.3.2 Birth Rate Parameters

- **Lower Birth Rate ($b_{\textbf{low}} = 0.1$)**: This rate represents the minimum birth rate necessary to sustain the population without causing rapid growth. It is applied in scenarios where the young agent proportion is above the threshold, indicating a relatively young and potentially growing population.
- **Normal Birth Rate ($b_{\textbf{norm}} = 0.2$)**: This is the standard rate used under typical conditions, designed to maintain a stable population size when the age structure is balanced.
- **Initial Birth Rate ($b_{\textbf{init}} = 0.25$)**: A slightly higher rate that is mostly used at the beginning of the simulation or when there are no agents that are alive. This rate assists in swiftly establishing an initial population to kickstart the ecological processes.

Appendix C

Proof of Non-Zero Population Maintenance

We aim to demonstrate that with an initial population of at least 10 agents and the carrying capacity equal to the initial number of agents ($N \geq 10$ and $K = N$), the population will not decline to zero as time approaches infinity.

C.1 Assumptions

The following assumptions are central to the model's design and functionality:

- **Initial Population**: The initial population size N_0 is set to 10, which is the lowest number tested. This size was chosen because anything lower would be seriously at risk of going extinct because of random population fluctuations.
- **Carrying Capacity**: The carrying capacity K is equal to the initial population size N_0, ensuring that the population dynamics are a result from birth and death rates (and not from any environmental constraints).
- **Birth Rate Adjustment**: The birth rate b adjusts dynamically based on the proportion of young agents (y), defined as follows:

$$b = \begin{cases} \max\left(b_{\text{low}}, b_{\text{norm}} - (y - \theta)\right), & \text{if } y > \theta \\ \min\left(b_{\text{norm}}, b_{\text{low}} + (\theta - y)\right), & \text{if } y \leq \theta \end{cases}$$

- **Death Rate**: Agents have a base death rate plus an additional rate that increases with age, reflecting age-dependent mortality risks.
- **Population Dynamics**: The number of agents at any given time t, denoted N_t, evolves according to the births and deaths within the model, governed by the stochastic nature of individual life histories.

This approach in setting the initial population size at the lower limit refines the model's sensitivity to parameter changes, providing a stringent test of the population's ability to sustain itself over time under minimal initial conditions.

C.2 Proof

We aim to show that the population cannot decline to zero given our dynamic birth rate setup.

Given that agents reproduce and die at certain rates, we need to demonstrate that the expected number of births meets or exceeds the expected number of deaths over time and therefore preventing the population from dying out.

1. **Minimum Population Maintenance**:
    - With $N_0 \geq 10$, the initial population is sufficiently large to provide a stable age distribution.
    - The birth rate b goes up when the proportion of young agents y is low, increasing the number of births.
    - The death rate increases with age, but with a balanced age distribution, not all agents will die simultaneously.
2. **Dynamic Birth Rate Adjustment**:
    - When the population decreases, the proportion of young agents y also goes down.
    - If $y \leq \theta$, the birth rate increases towards b_{norm} or even beyond if y is significantly low.
    - This increase in birth rate leads to more births, replenishing the population.
3. **Non-Zero Population**:
    - Even if the population starts to decline, the dynamic adjustment of the birth rate kicks in to ensure that more agents are born to recoup the population size.
    - Since the birth rate can increase up to $b_{\text{init}} = 0.25$ when no agents exist, the model introduces new agents to prevent the population from remaining at zero.
    - Therefore, the population size oscillates around the carrying capacity K but does not decline to zero.
4. **Conclusion**:
    - The mechanisms in place (dynamic birth rate, age-dependent death rate, and initial population size) collectively prevent the population from reaching zero.
    - Therefore, with $N_0 \geq 10$ and $K = N_0$, the agent population will not collapse to zero as time approaches infinity.

C.3 Limitations and Considerations

- **Stochastic Effects**: In a stochastic model, there is always a non-zero probability of extinction due to random fluctuations, especially in small populations. However, with $N_0 \geq 10$, this probability is minimised.
- **Model Parameters**: The proof assumes that the parameters remain constant and that the birth rate adjustments function as intended.

C.4 Mathematical Justification

To further substantiate the stability of the agent population, we analyse the expected change in population size ΔN_t at any given time t:

$$\Delta N_t = B_t - D_t$$

where B_t represents the number of births and D_t the number of deaths at time t.

- **Expected Births**:
  $$B_t = b_t \times (K - N_t)$$
  where b_t dynamically increases as N_t decreases below the carrying capacity K, encouraging population growth.
- **Expected Deaths**:
  $$D_t = d_t \times N_t$$
  where d_t is the average death rate, dependent on the age distribution of the population.

Given that the birth rate b_t is adjusted to increase when the population size N_t falls, which causes an uplift in higher birth rate, and considering that the death rate d_t remains fairly constant. The number of births we anticipate generally compensates for or exceeds the number of deaths. This dynamic ensures that N_t does not fall to zero.

Appendix D

Data Visualisations

D.1 Experiments - Plotting Different Runs

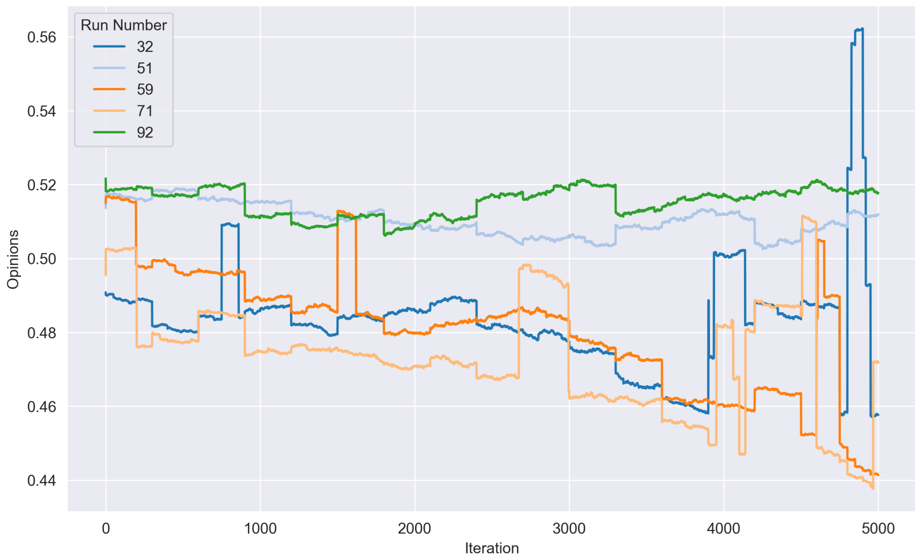

Figure D.1: Baseline experiment

D.2 Experiments - Opinion Distribution

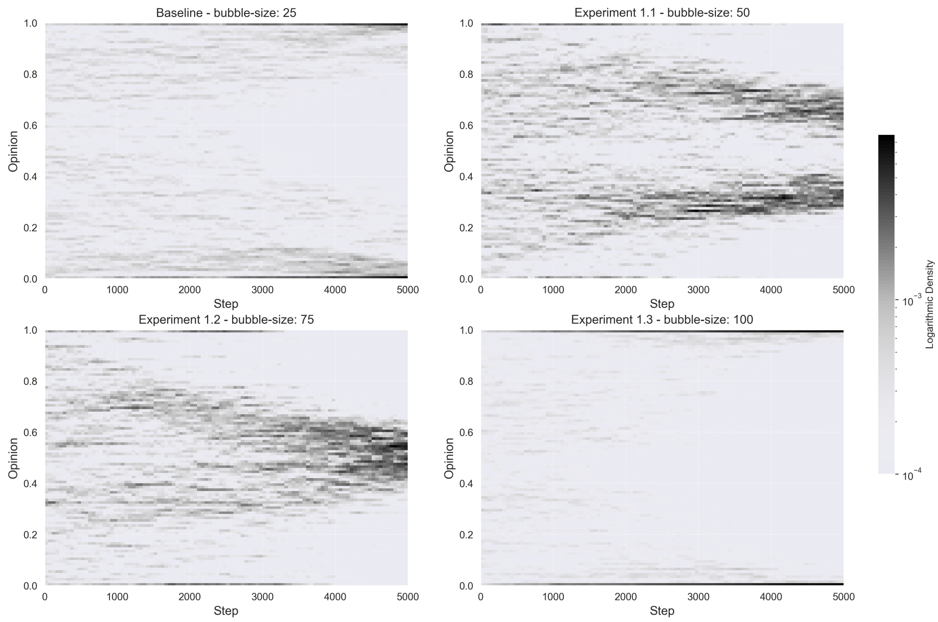

Figure D.2: Experiment 1: Varying Bubble-Size

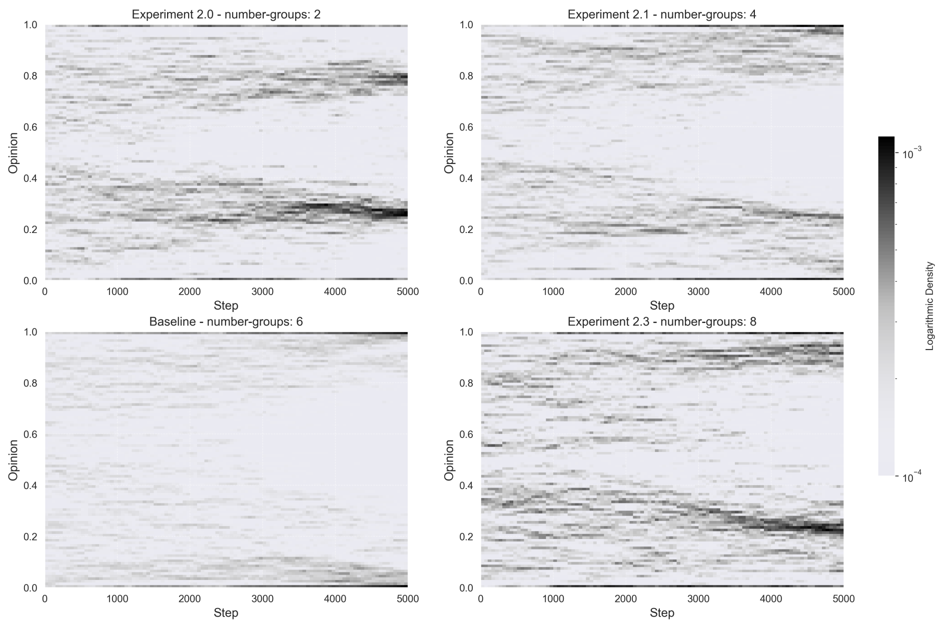

Figure D.3: Experiment 2: Changing Number of Groups

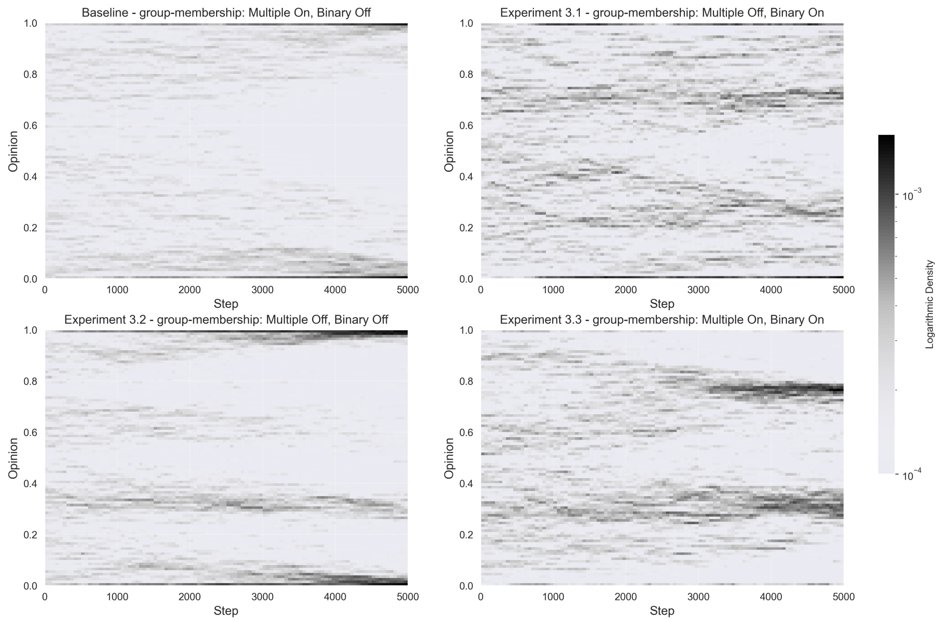

Figure D.4: Experiment 3: Group Membership Variations

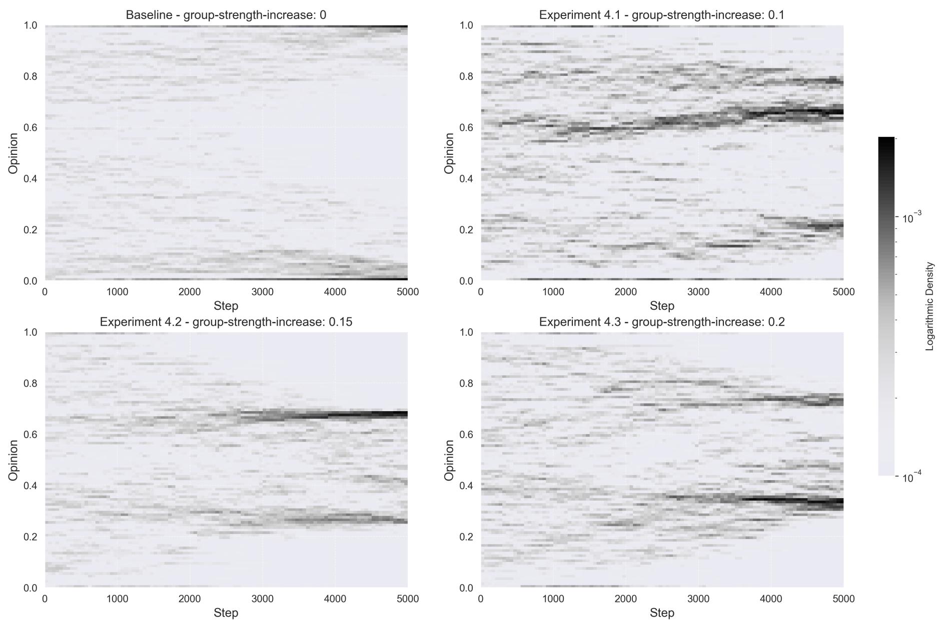

Figure D.5: Experiment 4: Varying Group Strength Increase

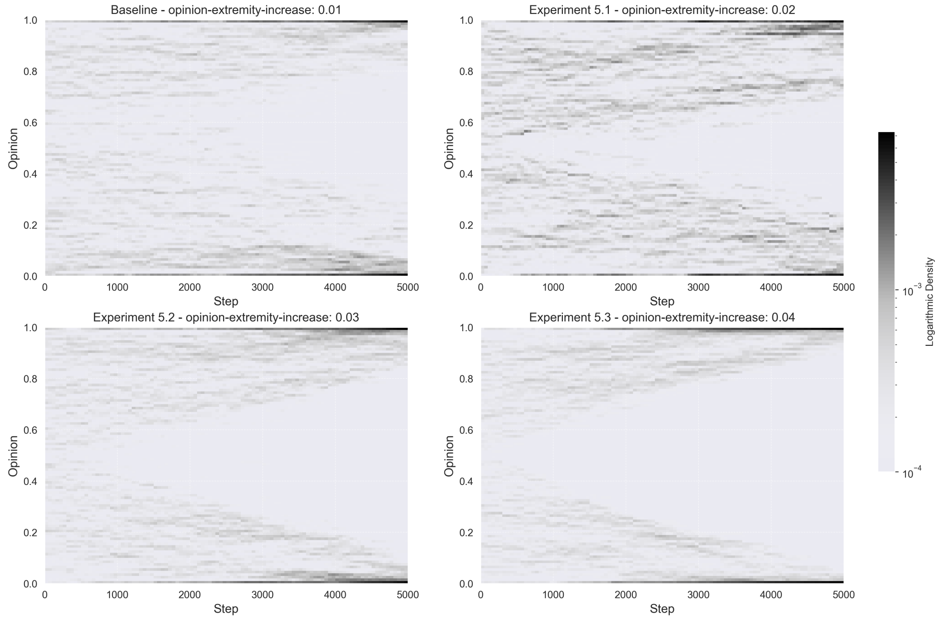

Figure D.6: Experiment 5: Varying Opinion Extremity Increase

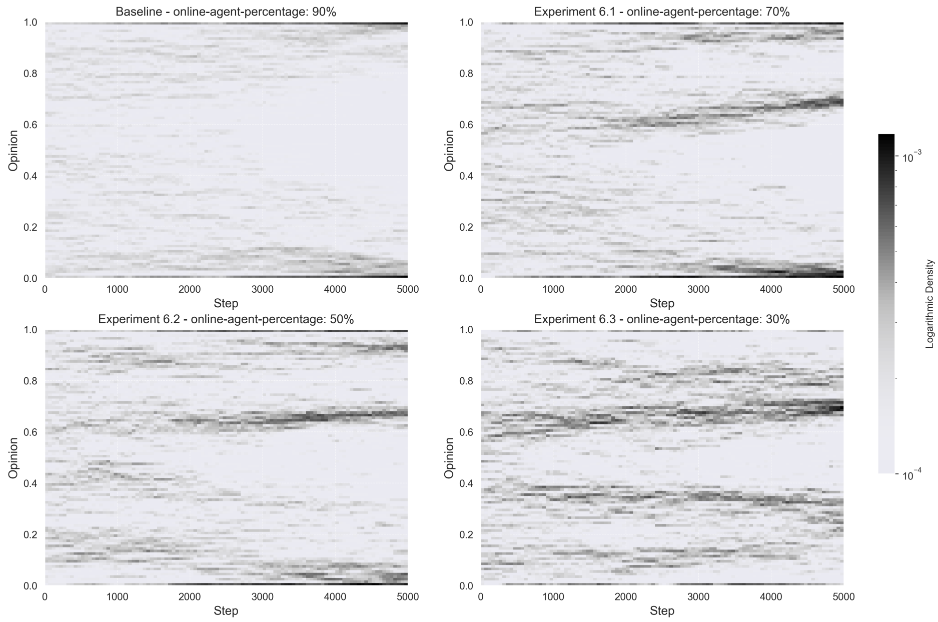

Figure D.7: Experiment 6: Changing Online Agent Percentage

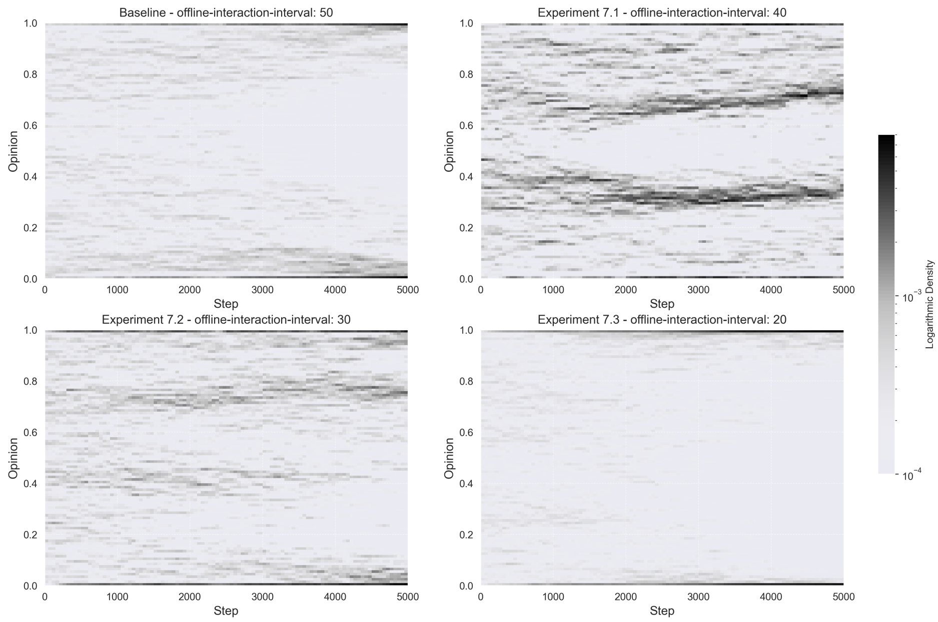

Figure D.8: Experiment 7: Changing Offline Interaction Interval

D.3 Experiments - Polarisation Metrics

D.3.1 Spread

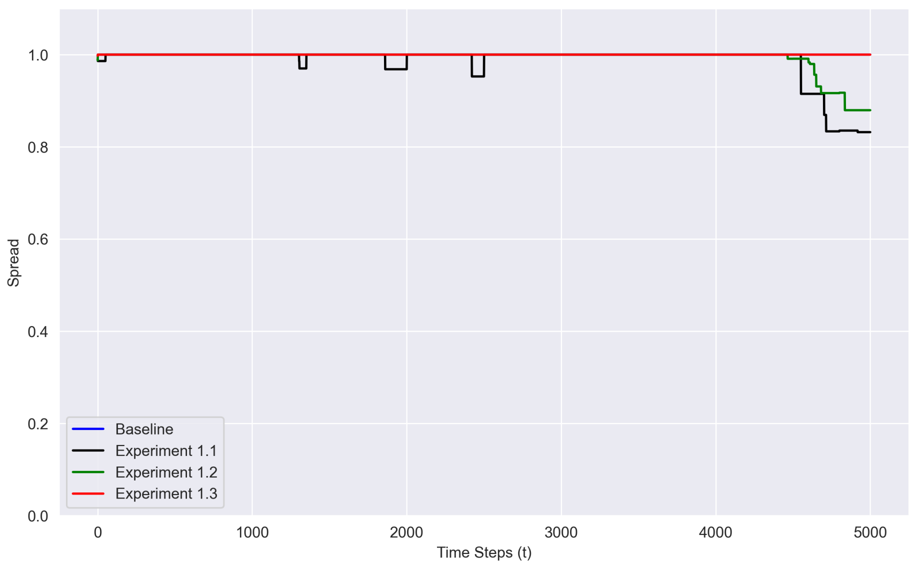

Figure D.9: Polarisation Spread - Experiment 1

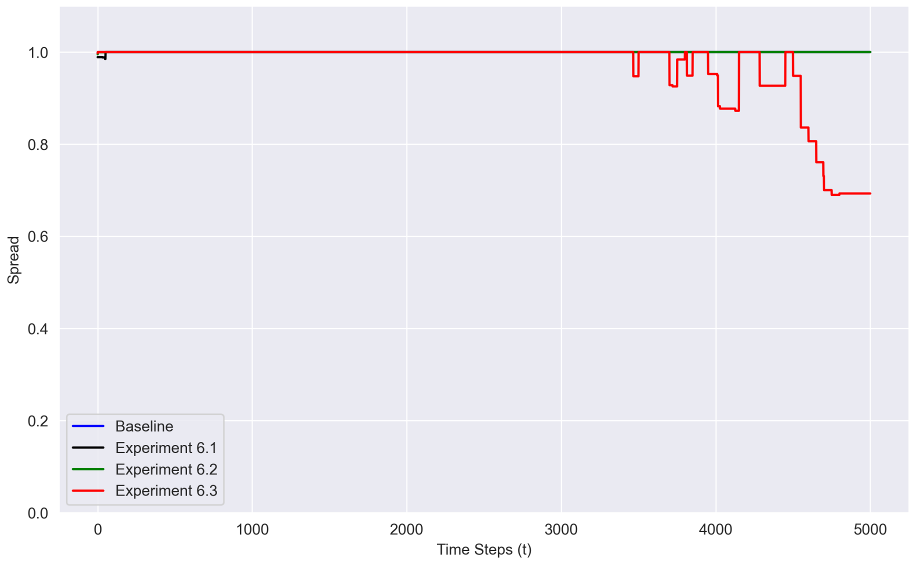

Figure D.10: Polarisation Spread - Experiment 6

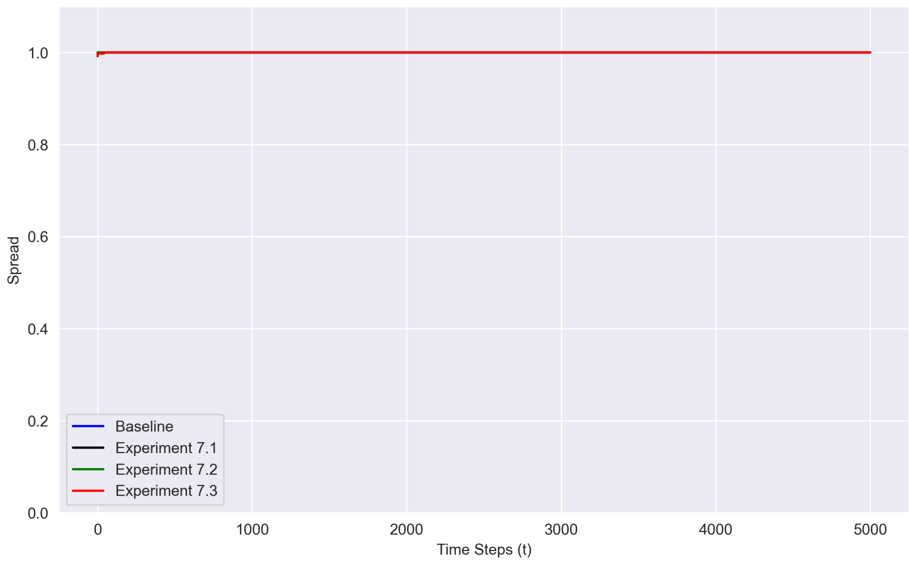

Figure D.11: Polarisation Spread - Experiment 7

D.3.2 Dispersion

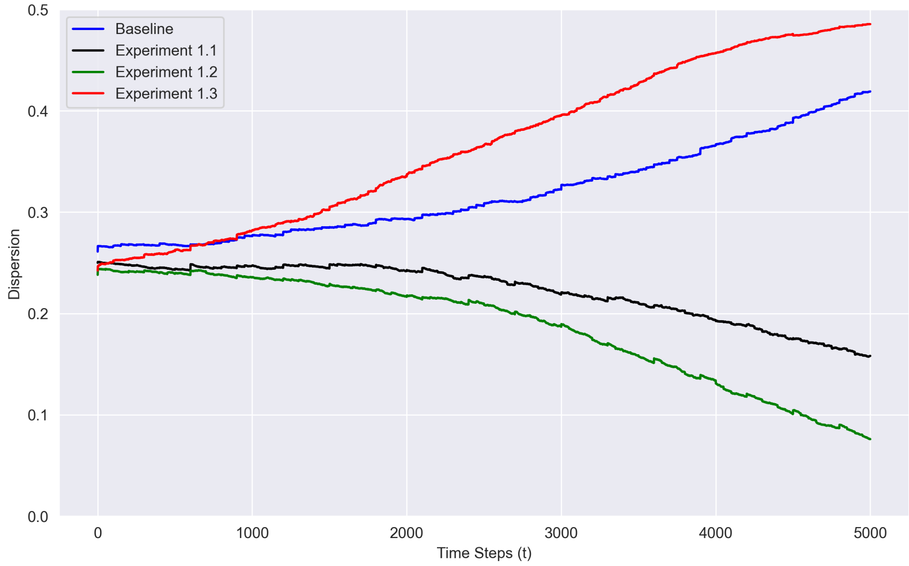

Figure D.12: Polarisation Dispersion - Experiment 1

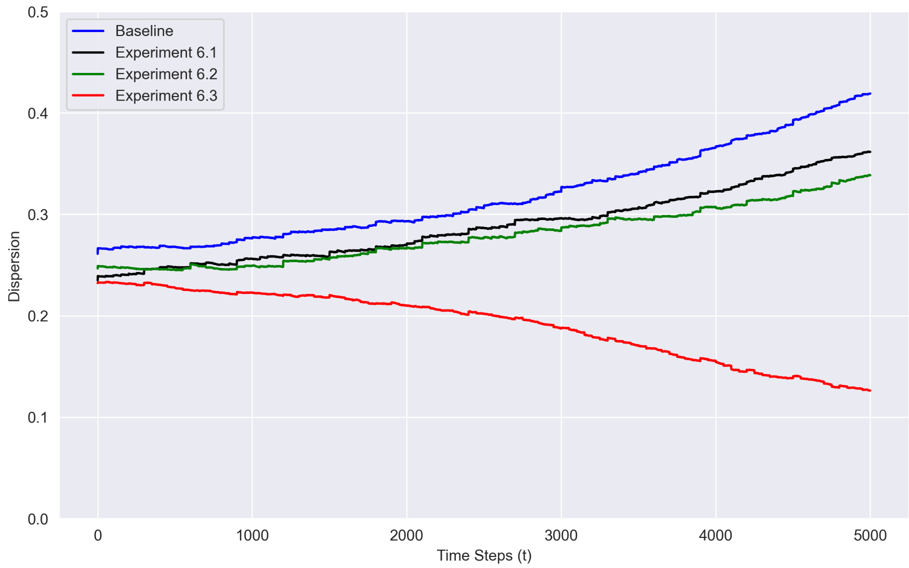

Figure D.13: Polarisation Dispersion - Experiment 6

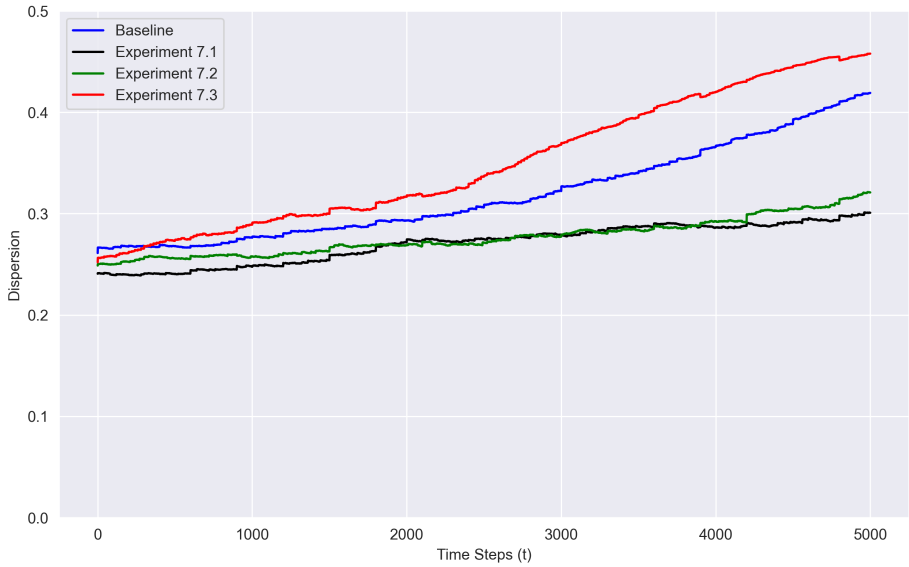

Figure D.14: Polarisation Dispersion - Experiment 7

D.3.3 Coverage

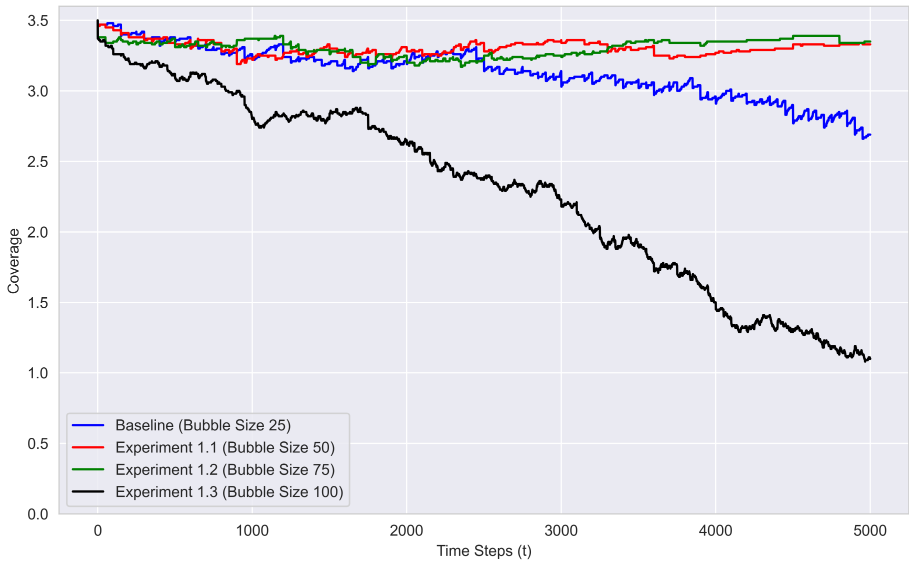

Figure D.15: Polarisation Coverage - Experiment 1

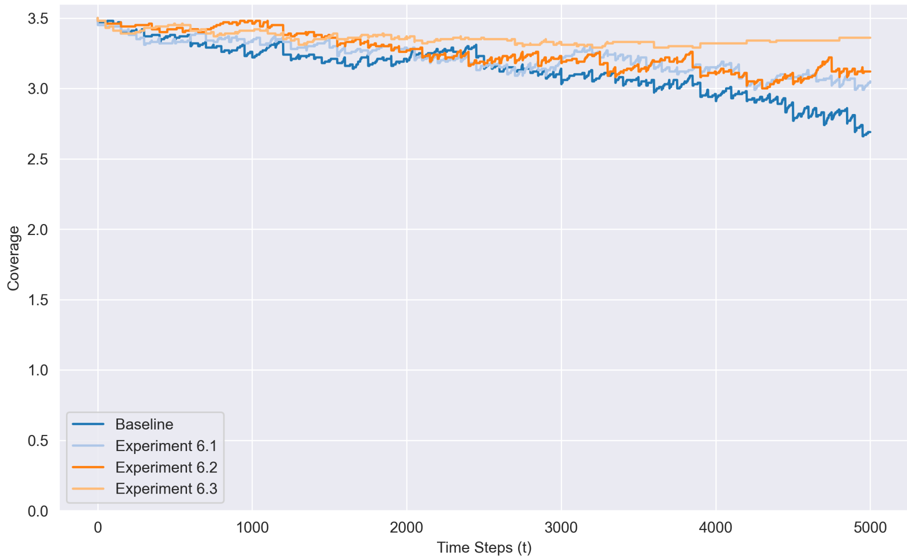

Figure D.16: Polarisation Coverage - Experiment 6

Figure D.17: Polarisation Coverage - Experiment 7

D.3.4 Entropy

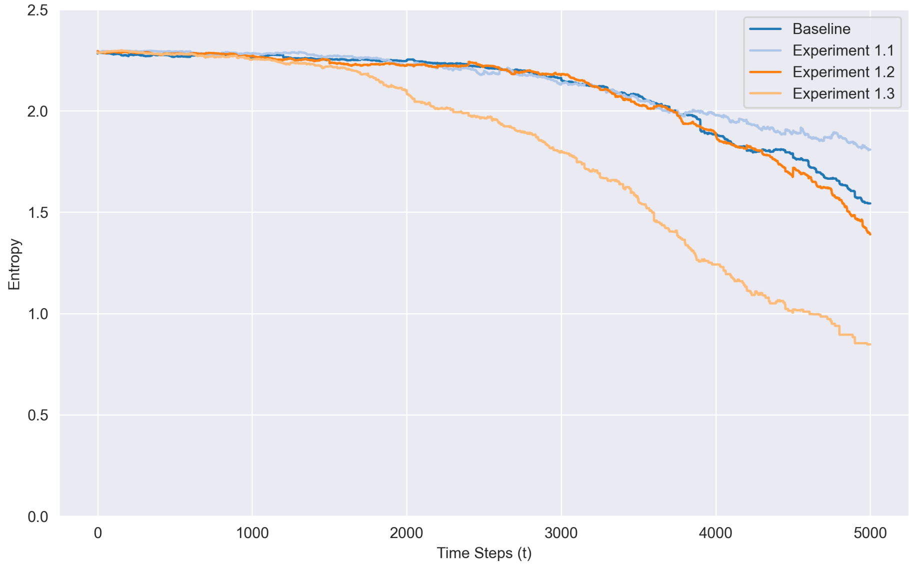

Figure D.18: Polarisation Entropy - Experiment 1

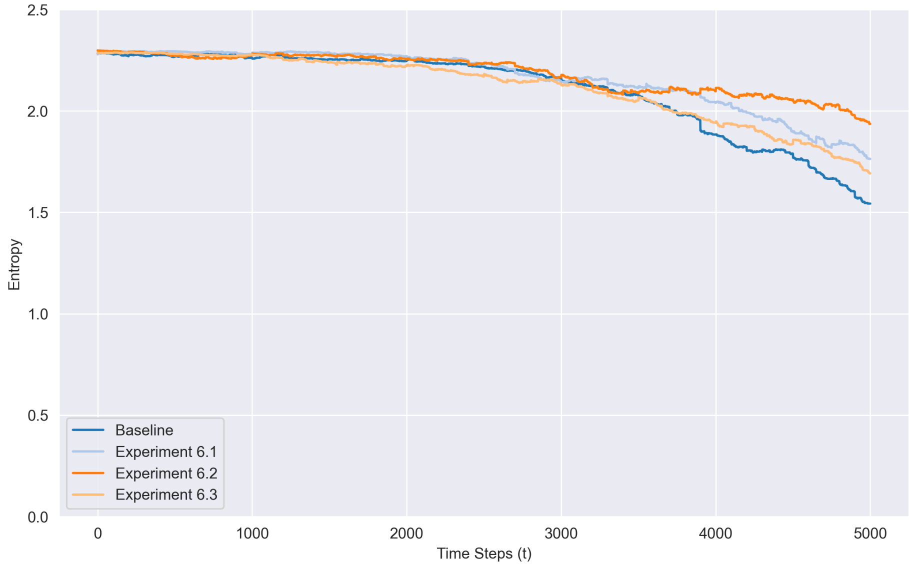

Figure D.19: Polarisation Entropy - Experiment 6

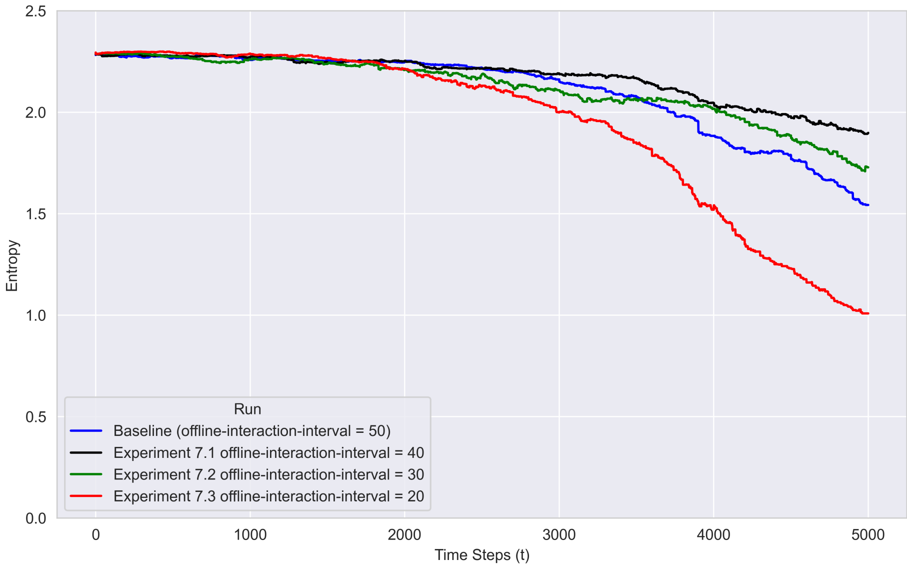

Figure D.20: Polarisation Entropy - Experiment 7