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Quantitatively modelling opinion dynamics during elections

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Abstract

Political advertising has become overwhelmingly focused on online platforms, with ever-improving capabilities of tailored and targeted advertising to individuals. Modelling the effect of political propaganda on a voting population has become more prevalent in opinion dynamics research, which has become further enabled by the applications of computer simulation and data analysis. In this study we explore the effect of propaganda on a voting population. The agent-based model describes a population of voter agents who hold a political opinion using knowledge and emotion as their control variables. These variables are updated through agent interactions and political propaganda. The model is based on the emotion/information/opinion (E/I/O) approach which is applied to a grid-based and network population. Furthermore, the network is programmed to be partially dynamic, in that connections between disagreeing agents can be severed under certain conditions concerning the intimacy of agent relationships. This is performed with the intention of adding more flexibility to the model, whilst making it a more realistic representation of reality. The different network types are shown to produce varying proportions of metastable agent states from identical starting conditions, which can be used to represent real political situations and predict future change.

Key words: micro-targeted campaigning; cognitive modelling; political messaging; computer simulation modelling

1 Introduction

The online advertising landscape has seen a wave of increased controversy and debate after the United States presidential election in 2016 — a year during which the amount spent on online advertising grew by an estimated 789%, reaching $1.4 billion. This was coupled with a 20% decrease in broadcast television advertising from the previous presidential

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cycle [1]. Concerns over the use of personal online data to fuel disinformation campaigns and other forms of media propaganda are at the forefront of the online-ethics debate [2]. In 2022, the world's big data and business analytics market is forecast to grow to $274 billion [3].

The utilisation of personal data for targeted advertising has contributed to the rise of global technology giants including Facebook, Alphabet, Apple, Microsoft and Amazon [4]. In the second quarter of 2019, Facebook alone generated $16.6 billion in advertising revenue, contributing to 99.6% of it's total revenue for the quarter [5]. In the last decade, the use of political advertising and *microtargeting* — where individual potential supporters are identified using various data mining techniques — has been the ethical crux of various scandals with the intention of influencing the opinion dynamics of voters [6].

Digital advertising has been likened to a *Digital Influence Machine* where personal information has been *weaponised* to strategically influence the vulnerabilities of the individual, particularly in the realm of politics [2]. Data points that describe users of online platforms inform a character profile that can facilitate microtargeting. Reportedly, Facebook uses over 52 000 attributes in classifying its users [7].

Former British political consulting firm, Cambridge Analytica, demonstrates the case for the influence of data-fuelled psychographic profiling in political advertising and the ethical concerns thereof. Well-known for their roles in using data analysis to provide services for Ted Cruz and Donald Trump's presidential campaigns as well as for pro-Brexit organisation Leave.EU in 2016, the firm became the subject of multiple criminal investigations surrounding their illegal acquisition and retention of up to 87 million Facebook users' personal data [8]. During political campaigns managed by the firm, tactics capitalising on bipartisan polarity through advertising aimed at tarnishing political opponents were used to influence voter perceptions. An example of this was the "Lock Her Up" campaign aimed at discrediting the 2016 American presidential candidate, Hillary Clinton.

The perturbing revelation by Facebook's chief security officer that during the period of June 2015 to May 2017 there had been an estimated $100 000 spent on advertising associated with approximately 3 000 advertisements linked to "Russian groups trying to influence the US elections" further underlined the ethical implications of online political advertising [9]. Special prosecutor Robert Mueller later provided evidence underpinning the Russian organisation, Internet Research Agency (IRA), as accountable [2, 10]. The IRA's advertising strategy involved pushing emotive content matter to heighten bipartisan tensions in the United States of America [11]. The types of issues targeted are shown in Figure 1.

Although the misappropriation of personal online data influencing opinion dynamics is widely documented, the true extent to which people's votes can be persuaded through these means and the nature of targeted propaganda dissemination is unknown. In the case of Cambridge Analytica, there are mixed opinions on the ultimate effectiveness of their tactics and its influence on election results [12].

There are multiple approaches to quantitatively gauge the effect that strategies like microtargeting may have on the opinion dynamics of a population in the context of an election. The increasing inclusion of social media platforms in the introduction and dissemination

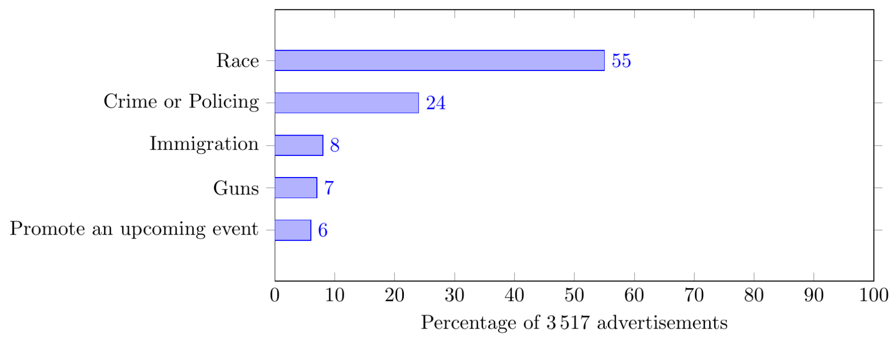


Figure 1: The top 5 election issues of Facebook advertisements commissioned by the IRA between June 2015 and August 2017 expressed as a percentage, as provided by USA Today [11].

of information throughout a networked population has informed various models describing information dissemination behaviour [13, 14]. Personal interactions between individuals and the nature thereof play an additionally important role in how voters' political opinions are informed.

Some of the more popular models offering insight into opinion states and interpersonal dynamics among a voting population include those of Cox and Griffeath [15], Ben *et al.* [16] and Castellano *et al.* [17] on the voter model, as well as approaches using the Sznajd model [18] and the Hegselmann-Krause model [19]. These models, however, are largely mathematical and are limited in their abilities to describe complex opinion dynamics and human behaviour over time in an analytical manner. Computer simulation and in particular, agent-based modelling (ABM), has allowed for the development of numerous models that accurately describe various phenomena in the field of voter dynamics [20, 21, 22, 23]. ABM's use of autonomous agents is ideal for modelling human behaviour and interaction, which could aid further understanding into the effectiveness of political persuasive techniques.

2 Modelling the effects of propaganda on a voting population

In analysing the effect of propaganda, an initial agent-based model is developed based on a study by Sobkowicz [23]. The aim of the original model by Sobkowicz [23] was to utilise the emotion/information/opinion (E/I/O) approach in simulating the election dynamics of the Polish political scene during 2005–2015 when a duopoly was broken down by a rapid emergence of a third party.

The agents represent the voting population, each of whom is described by three parameters, namely emotion, information and opinion. Here, emotion represents an agent's emotional involvement in an issue (in this case an election) and can be one of two states — calm or agitated. A calm agent is said to be open to external information and reasoning whilst still being able to formulate and express their own opinions. An agitated or excited agent is said to be emotionally charged, and thus struggles to accept new information. The information parameter represents the information that the agent holds regarding the issue, such as favouring a particular political party. The opinion parameter is a variable dependent on the other two control variables. This approach is based on a simplification of Zeeman's [24] description of catastrophe theory*. The two control variables, emotion and information, are respectively labelled as the *splitting* and *normal* factors.

The relationship between the emotion and information parameters that denotes the agent's state is based on Sobkowicz's interpretation of Zeeman's description of a cusp catastrophe model, where the state of mind is likened to a continuous plane. Sobkowicz [25, 23] presents a simplified interpretation, where the three variables are defined discretely, as shown in Table 1.

Variable	Discrete value	Description
Emotion	0	Calm
	1	Agitated
Information	1	Informed, favouring party X
	-1	Informed, favouring party Y
	0	Uninformed, no favour
Opinion	1	Pro party X
	-1	Contra party X
	0	Neutral

Table 1: The discrete states and descriptions of the emotion, information and opinion variables.

From these discrete states, there are seven possible E/I/O states that an agent can hold in a bipartisan election, as shown in Table 2. The symbols correspond to the possible E/I/O states, where the first of the three alphanumerical elements which constitute the symbol can be either 'C' or 'A' depending on whether the agent is calm or agitated, respectively. The second alphanumerical element is 'X' if the information held by the agent supports party X, 'Y' if the information supports party Y and '0' if the agent is uninformed. The third alphanumerical element thus represents the opinion state, and is similarly 'X' if in favour of party X, 'Y' if holding an opinion contra to party X, and '0' if neutral.

Symbol	Emotion	Information	Opinion
CXX	0	1	1
C00	0	0	0
CYY	0	-1	-1
AXX	1	1	1
A0X	1	0	1
A0Y	1	0	-1
AYY	1	-1	-1

Table 2: The states of agents in an E/I/O model based on their discrete emotional, information and resultant opinion states.

*A method describing how emotional state can lead to abrupt behavioural changes.

These possible E/I/O states are represented on the cusp catastrophe surface in Figure 2. It is evident that the central property of the cusp catastrophe is that it enables an agent to hold a contrasting opinion to another, despite having the same information on the issue. This feature is represented by the cusp catastrophe surface fold.

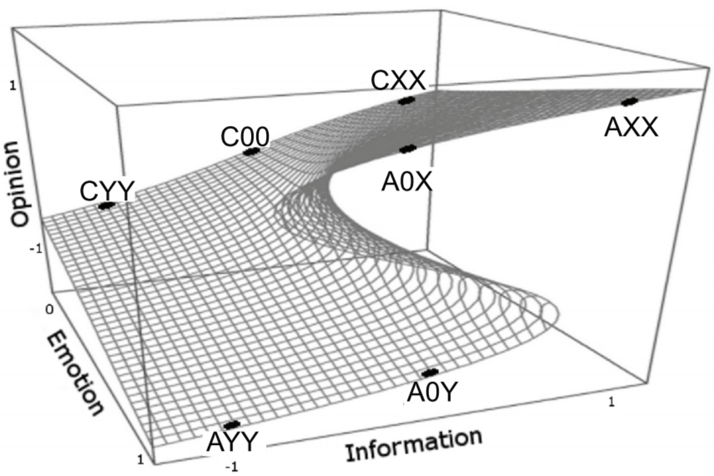


Figure 2: The discrete opinion states of the E/I/O model on the cusp catastrophe surface applied to a bipartisan election [25].

Agents interact *via* separate messages which contain information pertaining to the three variables. The data embedded in a message will include the current state of the agent sending the message. When an agent receives a message during interaction with another agent, the receiving agent's parameters may be updated, depending on whether they are calm or agitated. Calm agents are capable of changing their opinions, whereas agitated agents first need to be calmed down before being able to change opinion. Agitated agents can be calmed with probability p_{calm} when interacting with other agents who are either calm themselves or are in agreement with the agent. Conversely, a calm agent can also be agitated with probability p_{agit} when interacting with other agents who are either agitated themselves or hold an opposing view.

The influence of propaganda is an event modelled with the same messaging mechanism governing agent interaction. The information and emotion of the media messages correspond to the strategy of the propaganda, having a specific political leaning and end emotion. These messages are set to be more frequent and thus more influential than those of personal interactions, justified by the compelling nature of media and a social tendency to avoid sensitive topics of conversation.

Propaganda messages are divided amongst the competing parties and can fall in four possible categories, namely external rational, external irrational, internal mobilising and internal demobilising. Mobilising propaganda aims to strengthen favour with supporters by arousing agitation. Demobilising propaganda, often communicated unintentionally through poor execution, can bore supporters by decreasing their emotional commitment. Rational propaganda seeks to convince non-supporters to change allegiance through logical reasoning and policy exposure. Irrational propaganda occurs when rational propaganda backfires, further agitating non-supporters. A propaganda message can be in two categories simultaneously, *e.g.* mobilising to its supporters and irrational to its non-supporters.

As the study aims to qualitatively describe the emergence of a third party in an existing duopoly, the possible opinion states in the simulated case study increase from seven to ten. There is large possible variability deciding on the communication process, due to the mode of communication (one-to-one or one-to-many), the social network's topology, as well as the timing and frequency of communications. Sobkowicz [23] applies a 400×400 two-dimensional square geometry to situate the agents who can interact within a Moore spatial neighbourhood.

The simulation begins with agents at a neutral state, barring approximately one percent of 'seed' agents to represent the two dominant political parties. The agents are allowed to interact free from any propaganda until the system evolves into a stable state, where calm agents are surrounded by zones of similar opinion. At borders between zones of contrasting opinions, agents are agitated. Here the preparation phase is concluded with a steady-state duopoly and the third party can be introduced.

At this stage, parties are able to produce propaganda, with 80% of messages being propaganda and 20% being personal interactions between agents. Their marketing strategies are coded to correspond with the known strategies of the real parties in question.

As is expected in ABM, the Sobkowiz E/I/O agent-based voter model makes several assumptions that oversimplify the reality it is intending to replicate. Catastrophe theory in itself is a vast simplification of behavioural and psychological dynamics, compounded by the decision to discretise its cusp catastrophe surface. Having only two factors that drive the opinion change of an individual overlooks the possible impact of potential factors such as charisma, trust or reputation of the agent. There is also no inclusion of an individual's possible tendency to be a contrarian.

3 Method: an Agent-Based Model

The development of the proposed agent-based model is performed using the AnyLogic Personal Learning Edition 8.5.2 software suite, which is a cross-platform, multi-method simulation modelling tool that supports discrete event, system dynamics, and agent-based simulation methodologies. The software uses a Java-based object-oriented interface which allows for complex model development and visualisation [26]. The software's ease of model alteration through its graphical user interface and the extent of its ABM resources made it an appropriate software to develop the proposed model.

The model assumes a bipartisan system where the two conceptual parties are referred to as Party X and Party Y. The possible E/I/O states are modelled as discrete values, as described in the previous section. Individuals may never have an opinion that contradicts their information state. Furthermore, each voter has an equal likelihood of changing states upon interaction. Propaganda strategies are limited to the four categories of external rational, external irrational, internal mobilising, and internal demobilising. Parties have the capacity to reach any individual voter with their respective propaganda. Throughout a simulation run, the amount of voters is fixed and finite. Therefore, no voters can enter or exit the simulation environment. Voters can only interact within their configured neighbourhood.

3.1 An initial grid-based model

The agents interact within the main agent environment, which serves as the primary screen for a model user when executing a simulation run, as shown in Figure 3. The initial square geography that defines the space in which the voter agents are situated is similar to the model developed by Sobkowicz [27], being a 200×200 grid where agents interact within their Moore neighbourhood. This simulated environment is included in Figure 3 at (A), with the agent E/I/O states illustrated by means of a colour index, and the population size per E/I/O state included in the colour legend. The agent state proportions over time are illustrated using the graph at (B).

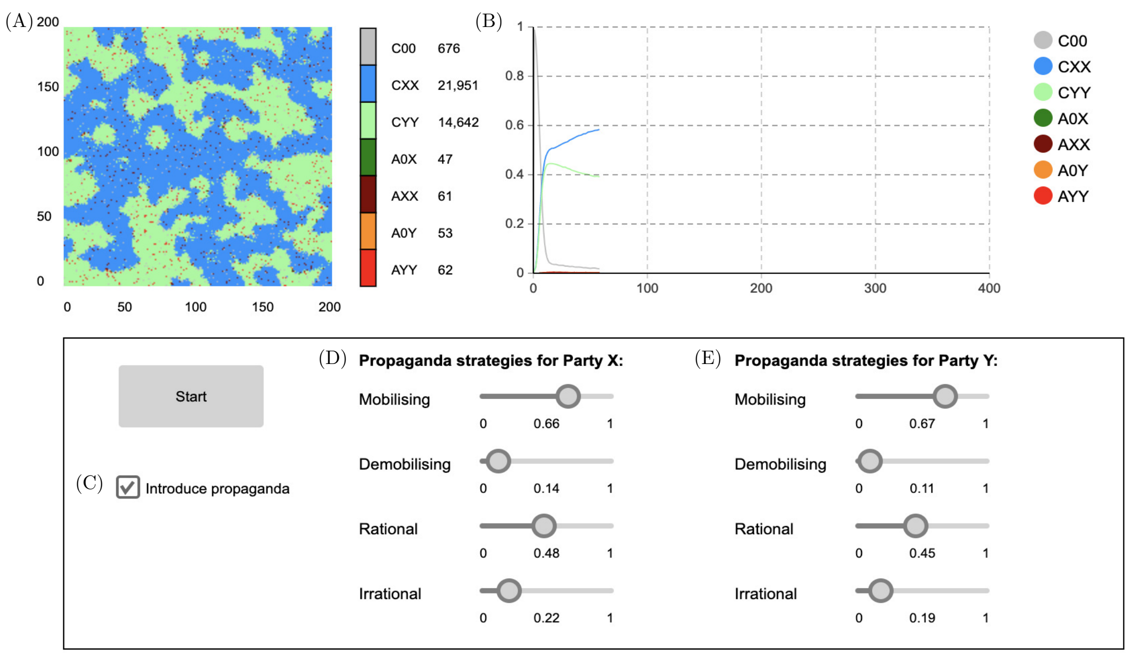


Figure 3: The primary screen providing an animated representation of voter agent E/I/O states during a simulation run.

The population of voter agents can interact with one another, with or without the inclusion of propaganda messages as determined by a boolean variable, which is linked to the user-input as shown in Figure 3 at (C). If true, a certain proportion of total interactions, p_{prop}, are propaganda messages and the remainder are normal interactions.

The proportion of each propaganda message type, denoting a party's campaign strategy, is stored in the variables X_m, X_d, X_r, and X_i for Party X's mobilising, demobilising, rational and irrational propaganda, respectively. Corresponding variables are also defined for Party Y. Values are allocated to these variables according to the user input, as shown in Figure 3 at (D) and (E).

Each voter agent is initialised as it enters the *Receiver* statechart, as shown in Figure 4, to achieve the starting population's E/I/O state. The default starting conditions replicate one of Sobkowicz's [27] original experiments, where one percent of the agent population are set to be calm with randomly assigned information and opinion state values of both either set to 1 or -1 (*i.e.* either CXX or CYY). The remainder of the population are set to be calm and neutral with information and opinion state values of 0 (*i.e.* C00).

Voter interaction is modelled using two statecharts for receiving and sending messages, respectively. In each statechart, an agent occupies a 'state of being' until it is triggered into transitioning states. A voter agent in the *Sender* statechart migrates to the *Sending* state according to a rate trigger of once per day. Once in this state, the agent may be prompted to send a message to a random neighbour, triggering the message recipient into the *Evaluate* state of the *Receiver* statechart, which is shown in Figure 4. The agent acting as sender then transitions back to the *State of Being* state after one simulated minute.

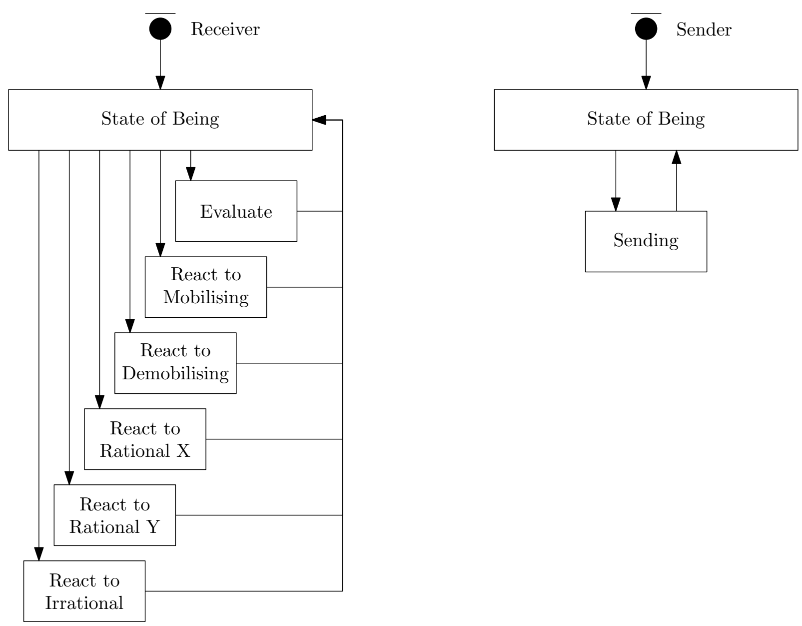


Figure 4: The voter agent statecharts in the proposed model.

In the *Evaluate* state, the receiving agent evaluates its own E/I/O variables based on the sender agent's E/I/O variables. A set of functions govern the outcomes of these interactions, which is summarised in Table 3, wherein bold states indicate a change in opinion. The E/I/O state interactions in Table 3 also holds for initial agent states corresponding to Party Y. The probabilities of agitation or calm, p_{agit} and p_{calm}, denote any agent's likelihood of becoming agitated or calmed during specific interactions. After evaluating and possibly updating their E/I/O variables, the receiving agent returns to the *State of Being* state after one simulated minute.

An agent's support status (pro Party X, pro Party Y, or neutral) is stored and updated whenever a change in opinion through interaction occurs. When propaganda messages are enabled, they are sent to agents at a proportion p_{prop} of total interactions. Propaganda

	Sender state	C00	CXX	AXX	A0X
	C00	-	-	CXX	CXX
Same party senders	CXX	**CXX**	-	CXX	CXX
	AXX	-	-	-	-
	A0X	-	-	-	-
Opposing party senders	CYY	**CYY**	AXX (p_{agit}) **C00** ($1 - p_{agit}$)	A0X ($1 - p_{calm}$) **C00** (p_{calm})	- ($1 - p_{calm}$) **C00** (p_{calm})
	AYY	-	A0X	A0X	-
	A0Y	-	AXX	-	-

Table 3: The resultant E/I/O states of voter agents after having received a message from another agent acting as a sender where bold states indicate a change in opinion.

	Message origin and type	C00	CXX	AXX	A0X
Same party messages	Demobilising message	-	**C00**	CXX	CXX
	Mobilising message	-	AXX	-	-
Opposing party messages	Rational message favouring Y	**CYY**	AXX (p_{agit}) **C00** ($1 - p_{agit}$)	-	-
	Irrational message favouring Y	-	AXX	-	-

Table 4: The resultant E/I/O states of voter agents after having received a propaganda message where bold states indicate a change in opinion.

messages are governed when an agent enters the *Sending* state. This ensures that the proportion of normal interactions to propaganda messages can be configured easily.

When an agent receives a propaganda message, it enters the relevant *React* state in the *Receiver* statechart. The *React to Mobilising* state relates to the mobilising strategy from either party. The *React to Demobilising* state relates to the demobilising strategy from either party. The *React to Rational X* state relates to the rational strategy from Party X, while the *React to Rational Y* state relates to the rational strategy from Party Y. Lastly, the *React to Irrational* state relates to the irrational strategy from either party. In each of these states, the agent evaluates its E/I/O variables in a process summarised in Table 4 where bold states indicate a change in opinion.

A schematic view of the process triggered when an agent enters the *Sending* state is provided in Figure 5. This process occurs once per simulated day.

3.2 Extending the model: Network and cut-edge mechanism

In reality, social interactions mimic a dynamic network far closer than a static two-dimensional grid [28]. People tend to operate within a social network, comprising of intimate connections (such as family) that are scarcely broken, and more superficial connections (such as work colleagues) that can be severed. The proposed model is consequently extended to allow for personal interactions to take place in a dynamic network that closer resembles reality. The extension involves two major adjustments to the model,

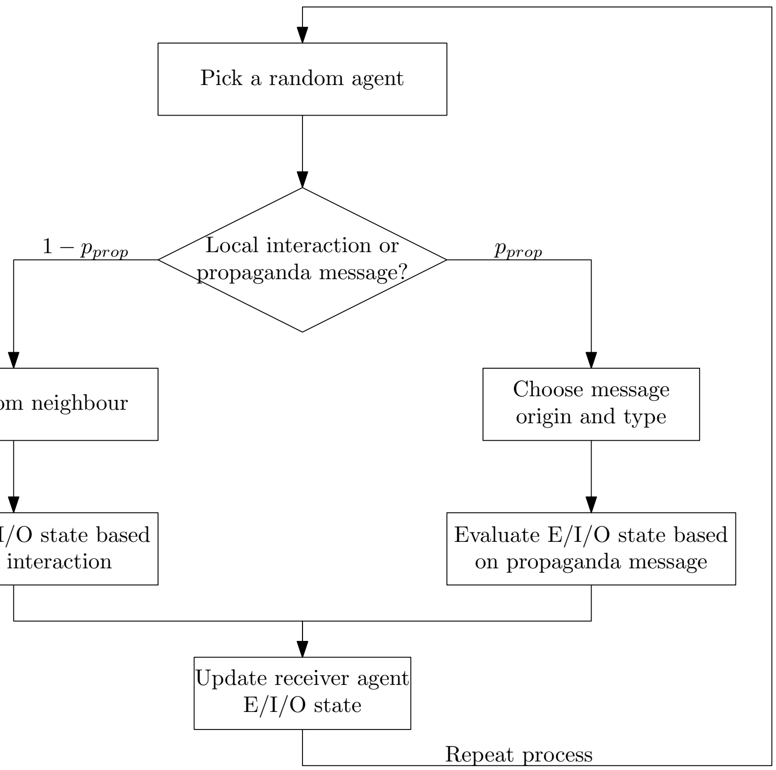


Figure 5: A schematic view of the process governing voter interactions and propaganda adapted from Sobkowicz [23].

the first being the redesign of the model in a continuous space, instead of discrete, allowing for a network and the second being an additional cut-edge mechanism.

A continuous environment allows for the modelling of agents connected in a network. In AnyLogic, the user is able to specify the type of network connecting the agents. The network types chosen for this extension include random, distance-based, ring lattice, and small world networks. In a random network, agents are randomly connected and each agent has an average number of connections. A distance-based network connects agents within a certain spatial proximity. A ring lattice, on the other hand, has agents form a ring in which a certain number of closest agents connect, while a small world network is a ring lattice where some connections have been changed to long distances.

The second adjustment is the inclusion of a *cut-edge* mechanism through which an agent may sever a connection with a superficially connected agent after disagreeing with them. Voter agents hold a proportion of intimate connections which cannot be severed. It is assumed that individuals would consider severing a connection when interacting with a superficially connected agent whose opinion is the opposite of their own. An agent's consideration of severing a connection only occurs when they become agitated. For example, an agent that was initially in a calm state and may become agitated with a probability p_{agit}, will therefore only consider severing a connection according to the probability p_{agit}. Similarly, when there is an interaction where an initially agitated agent might be calmed with a probability p_{calm}, it will only consider severing the connection with probability $1 - p_{calm}$.

The proposed extended model facilitates this by having an agent sever a superficial relationship according to a certain probability when receiving a message that results in the agent entering an agitated state. Each voter's connected agents, the degree of intimacy for each connection (0 for intimate connections and 1 for superficial connections), and a count of the number of interactions per connection is stored and updated in an array. Upon each voter-voter interaction where there is disagreement, the model updates the array and only cuts the connection with probability p_{cut} if the agents are superficially connected and have had a number of interactions with opposing opinions that is greater than a certain cut-edge threshold γ. The probability p_{cut} corresponds to the degree of intimacy for the connection, *i.e.* for intimate connections $p_{cut} = 0$ and for superficial connections $p_{cut} = 1$. A schematic illustrating this process is provided in Figure 6.

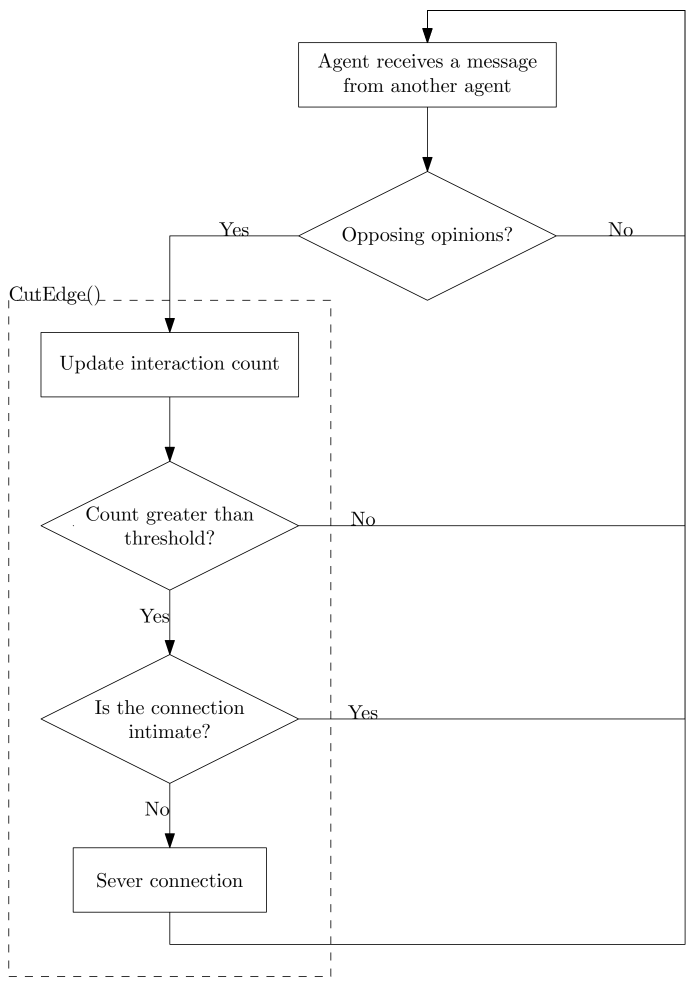


Figure 6: A schematic view of the process governing the cut-edge mechanism.

Sutcliffe *et al.* [29] describe the personal social network as a series of layers in which the degree of intimacy and number of relationships vary, referred to as 'circles of acquaintanceship'. These layers expand from the individual, or ego, and decrease in intimacy as the number of relationships within each degree increases, as shown in Figure 7. The first two layers are referred to as the support clique and sympathy group, respectively, and comprise an individual's intimate relationships. The outermost two layers are known as the affinity group and the active layer, representing more superficial relationships. As the number of relationships in each layer consistently scales by a factor of 3 [29], it is appropriate to say that, on average, approximately 10% of an individual's relationships can be described as being more intimate. This motivates allocating a value of 0.1 to the proportion of intimate connections in the proposed model.

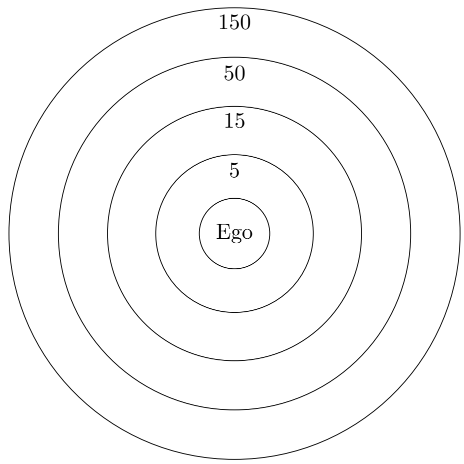


Figure 7: The layers of an individual's social network varying in intimacy and number of relationships [29].

Upon initiation of a simulation run, the model user can specify a population size and the network type which defines how the agents are connected. The population size corresponds to the number of voter agents initiated for a specific simulation run. After completing the user inputs required in the configuration screen, the user is brought to the primary screen shown in Figure 8. This graphical user interface includes three dynamics graphics — labelled (A), (B), and (C) — which illustrate the simulation.

The panel below the graphics allow the user to interact with the simulation. Sliders are included for each party's propaganda strategies, and are linked to the propaganda variables. By clicking the 'Start' button, the user begins the simulation run. During a simulation run, checking the 'Introduce propaganda' checkbox will cause propaganda messages at the normalised proportion set by the propaganda strategies to be sent to random agents. The proportion of propaganda messages p_{prop} can also be adjusted using a slider labelled 'Pprop'.

The population of voter agents is animated at (A), which shows the E/I/O state of each agent at the current timestep as well as their respective connections to other agents. Graph (B) shows the total number of voters for Party X, for Party Y, and neutral voters. Graph (C) shows E/I/O agent state proportions.

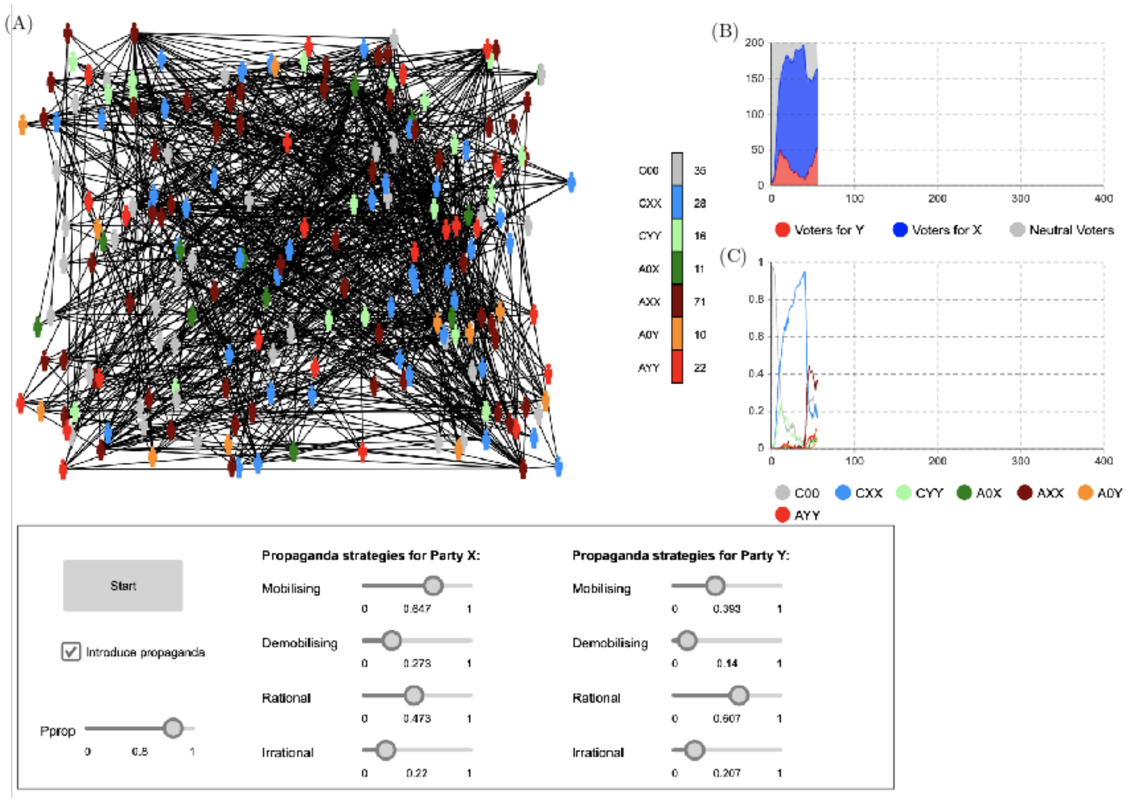


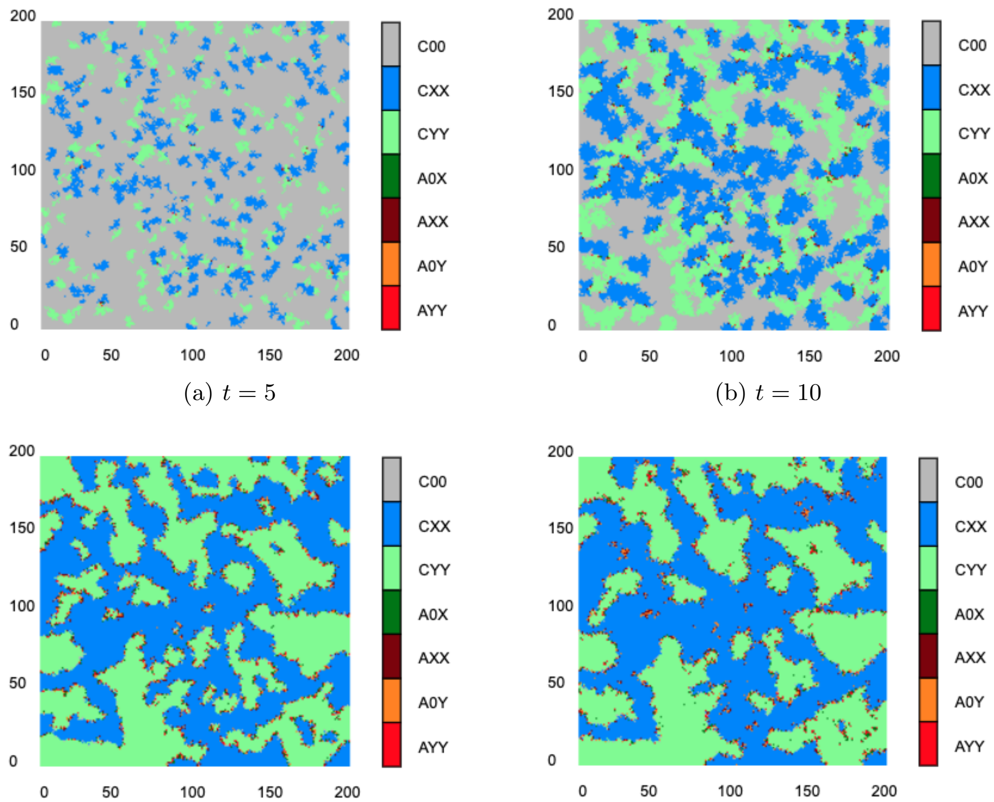
Figure 8: The graphical user interface's primary screen.

4 Simulation results

The initial grid-based model, as well as the extended network-based model, is considered in analysing the model output in this section. For the grid-based model, the simulation evolution is considered, along with a sensitivity analysis on the proportion of interactions between propaganda and voter messages, and, finally, the parameters governing the population's tendency to become agitated or calmed are calibrated. For the extended network-based model, a parameter variation is performed to investigate the cut-edge threshold. Furthermore, the different network types are analysed in considering the effect of the selected network type on the evolution of the population's E/I/O states in the proposed model.

4.1 Results from the grid-based model

The simulation evolution for the initial model applied to a grid-based population is captured in Figure 9 at four distinct times, namely at $t = 5, 10, 50$, and 300, where the rate of messages received per agent is one per timestep. The starting conditions are that all agents are initially calm, with 1% of agents being randomly assigned an opinion of 1 or -1. The parameters, $p_{agit} = 0.5$, $p_{calm} = 0.0$, and agents interact with their Moore neighbourhood. It is apparent that clusters of identical opinion form around the seed agents at $t = 5$, and at $t = 10$, larger clusters of like-opinions begin to form and there is more contact between clusters of agents with opposing opinions. Growth then appears to slow down when comparing the output at $t = 50$ to the output at $t = 300$, although agitated conflict boundaries are observed surrounding minority clusters.



(a) $t = 5$ (b) $t = 10$

(c) $t = 50$ (d) $t = 300$

Figure 9: Snapshots of the grid-based model system evolution at four distinct times.

Similarly, visual output can be observed when considering the long term evolution of agent state ratios. The ratio of agent states until $t = 1000$ is shown in Figure 10 for an experiment with the same starting conditions. The output displays three distinct chronological stages. First, an initial growth of calm, opinionated individuals in a mostly uninformed society (noted from initiation to approximately $t = 20$) is observed. This is followed by an intermediate stage involving conflict between the two opposing views, resulting in a particular view becoming the majority and the other the minority (noted approximately where $t_i < t < t_j$). And finally, a stable state is observed with a calm majority and two, virtually equal agitated and conflicted groups (noted where $t > t_j$).

The proportion of interactions between propaganda and voter messages can be based on the type of society to which the model is applied. An analysis of this ratio p_{prop} is thus performed to demonstrate the sensitivity thereof. This also aids in allowing the user to make an insightful decision regarding the activeness of the propaganda strategies. For this experiment, an arbitrary propaganda strategy is selected, as described in Table 5. Party X's propaganda strategy is chiefly external rational, with some unintended internal demobilising effects. Party Y's strategy is internal mobilisation, having some irrational

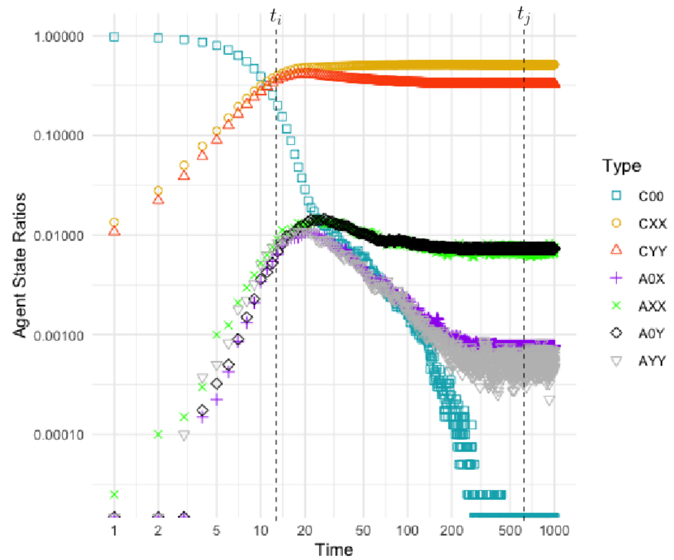


Figure 10: Long term evolution of agent state ratios for the grid-based model.

external effects. The interaction parameters are set as $p_{agit} = p_{calm} = 0.2$. Similar to voter-voter interaction, the rate of messages sent each timestep signifies the amount of time, on average, an agent takes to receive a message. Again, each simulation run starts at T_0 with 1% of randomly located opinionated seed agents surrounded by neutral agents. All agents interact within their Moore neighbourhood until a metastable social division is formed, as shown in Figure 11, where groups of calm, partisan agents are formed with a mixture of all other possible states at their boundaries. This signifies the 'real' starting condition observed at T_1 where $t = 200$.

Propaganda type	Party X	Party Y
Internal mobilising	0.00	0.40
Internal demobilising	0.10	0.00
External rational	0.25	0.00
External irrational	0.00	0.05
Total	0.35	0.45

Table 5: Propaganda strategies for an experiment.

At T_1, party propaganda messages are introduced for each of the four experiments where the proportion is set to $p_{prop} = \{0.60, 0.70, 0.80, 0.90\}$. The starting conditions are equivalent for all four experiments. The change in agent state ratios for each experiment run until T_2 where $t = 300$ is shown in Figure 12. Each experiment reaches a state where most Party X supporters remain calm, and most Party Y supporters have become agitated. This is expected, considering the external rational focus of Party X's propaganda strategy converting calm Party Y supporters, and the internal mobilising focus of Party Y's strategy converting calm supporters into agitated ones.

For each experiment, the introduction of propaganda has a drastic effect on the agent state ratios, the extent to which is linked to the proportion of propaganda introduced. The rate

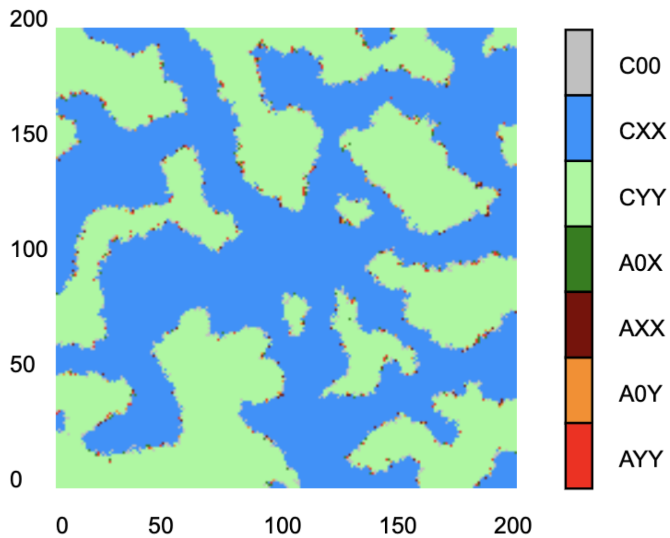
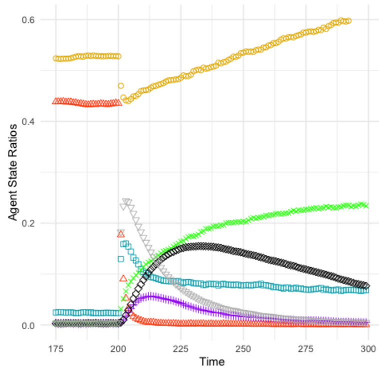
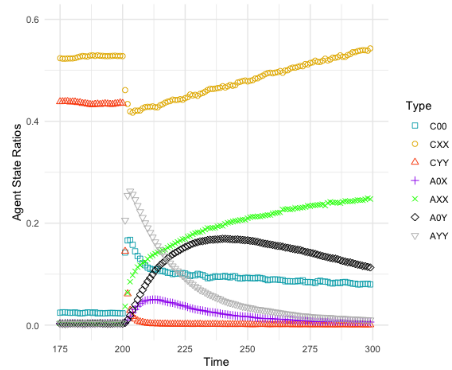


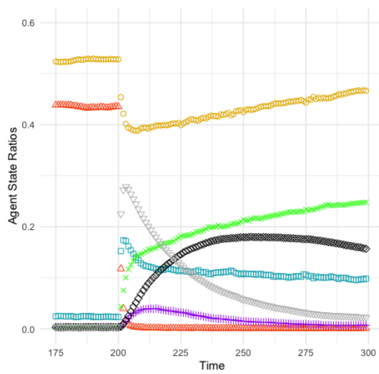
Figure 11: Snapshot of the social division developed in the absence of propaganda at T_1 in the grid-based model.



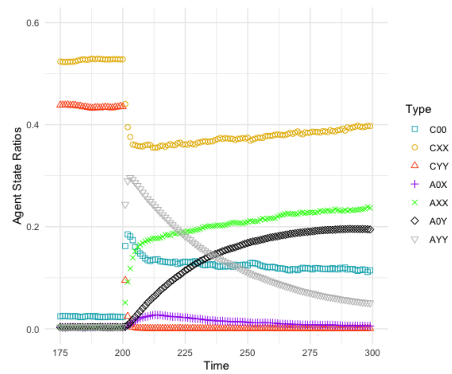
(a) $p_{prop} = 0.60$



(b) $p_{prop} = 0.70$



(c) $p_{prop} = 0.80$

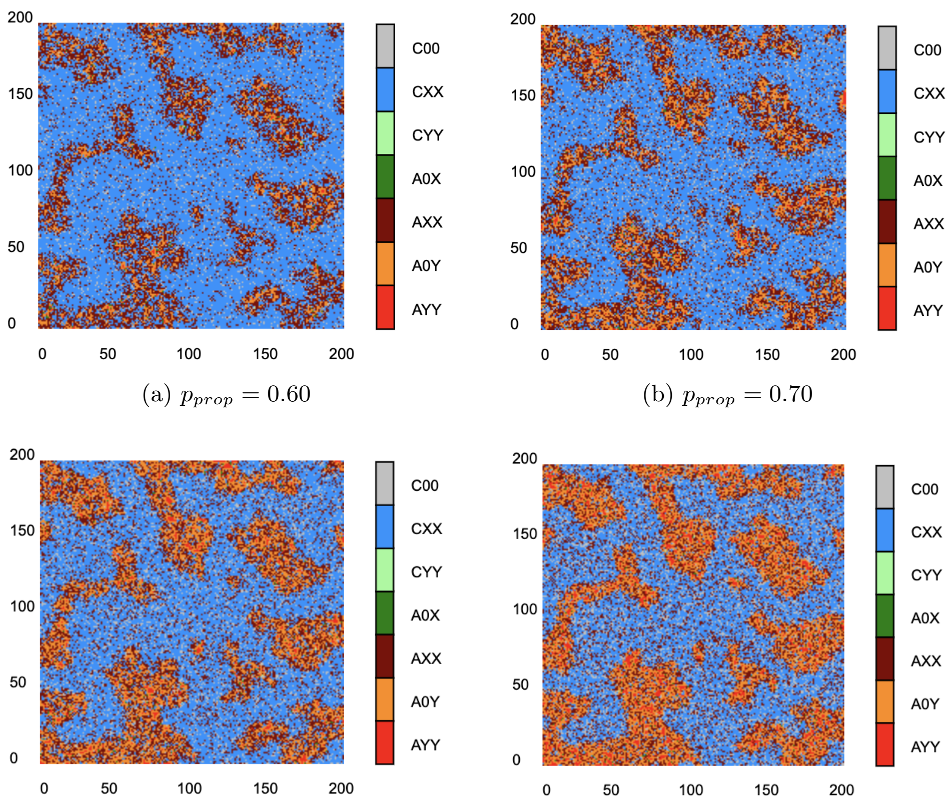


(d) $p_{prop} = 0.90$

Figure 12: Agent state ratios for different values of p_{prop} where propaganda is introduced at T_1 until T_2 in the grid-based model.

at which each possible E/I/O state changes differs slightly depending on the value p_{prop}. The initial change is proportionate to the value p_{prop}, thereafter various points of interest are observed. The lower the p_{prop} value, the faster the growth of CXX agents. This could be due to more opportunities for CXX agents to coerce their disagreeing neighbours to become calmed and then develop support for Party X, being the majority. Interestingly, a greater proportion of AOY agents are observed with a greater p_{prop} value, despite the AOY state not being a result of any interactions with the current propaganda strategies.

A different perspective of the agent states is shown in Figure 13, where snapshots of the agent model canvas at T_2 for each of the experiments conducted are provided. Here, the effect of propaganda on clusters of support groups is observable. Party Y's significantly more aggressive propaganda strategy, at least in comparing its message proportion to that of Party X, benefits greatly from a greater p_{prop} value. Party X's strategy, which focuses more on converting supporters of their opponent, infiltrates the clusters of Party Y supporters and dissolves them through word of mouth.



(a) $p_{prop} = 0.60$ (b) $p_{prop} = 0.70$

(c) $p_{prop} = 0.80$ (d) $p_{prop} = 0.90$

Figure 13: Snapshots of the agent model canvas at T_2 for different values of p_{prop} introduced at T_1 in the grid-based model.

The parameters p_{agit} and p_{calm} represent a population's tendency to become agitated or calmed during certain interactions. A calibration of these two parameters in the form of a full factorial design is displayed in Figure 14 where the ratio of agents per state is shown at different values for each parameter. Both parameters range from 0.1 to 0.9 in

Experiment	p_{agit}	p_{calm}	Experiment	p_{agit}	p_{calm}
(a)	0.1	0.1	(n)	0.5	0.7
(b)	0.1	0.3	(o)	0.5	0.9
(c)	0.1	0.5	(p)	0.7	0.1
(d)	0.1	0.7	(q)	0.7	0.3
(e)	0.1	0.9	(r)	0.7	0.5
(f)	0.3	0.1	(s)	0.7	0.7
(g)	0.3	0.3	(t)	0.7	0.9
(h)	0.3	0.5	(u)	0.9	0.1
(i)	0.3	0.7	(v)	0.9	0.3
(j)	0.3	0.9	(w)	0.9	0.5
(k)	0.5	0.1	(x)	0.9	0.7
(l)	0.5	0.3	(y)	0.9	0.9
(m)	0.5	0.5			

Table 6: Parameter values for each full factorial design experiment shown in Figure 14.

increments of 0.2 such that p_{calm} increases from left to right and p_{agit} from top to bottom in the figure. The values of p_{agit} and p_{calm} for each experiment in Figure 14 are included in Table 6 for reference. For each experiment, the starting state of the population had 1% calm, opinionated seed agents with the remainder in state C00.

Observations can be made regarding the effect of these parameters on the agent state ratios, primarily on the rate of change of calm, uninformed (C00) agents, and agitated (A0X, AXX, A0Y, AYY) agents. In Figure 14, the proportion of C00 agents tends to decrease faster with larger p_{agit} values, and slower with larger p_{calm} values. The same is true for agitated agents. Intuitively, it would appear that larger p_{agit} values correlate with a higher peak of agitated agents. Moreover, a larger p_{calm} value tends to create a gap between the larger proportioned informed, agitated (AXX, AYY) agents, and the lesser proportioned uninformed, agitated (A0X, A0Y) agents. The deficit seems to be reflected in a larger gap between calm supporters (CXX, CYY) of the majority and minority parties.

4.2 Results from the extended network-based model

The extended network-based model allows for more abstract phenomena to be observed in modelling the behavioural aspect of agents to more closely resemble reality. Further model flexibility is developed through a graphical user interface.

The cut-edge mechanism, and its dependence on a degree of intimacy for each connection, is intended to replicate one's desire to avoid extended conflict. In reality, most people would not persist in maintaining a superficial connection with another if there is repetitive disagreement. This threshold would vary from person to person, motivating the need for a distribution of varying thresholds throughout the population. Moreover, the desire to maintain intimate connections tends to supersede political disagreements for the most part, which is why these connections cannot be severed in the model.

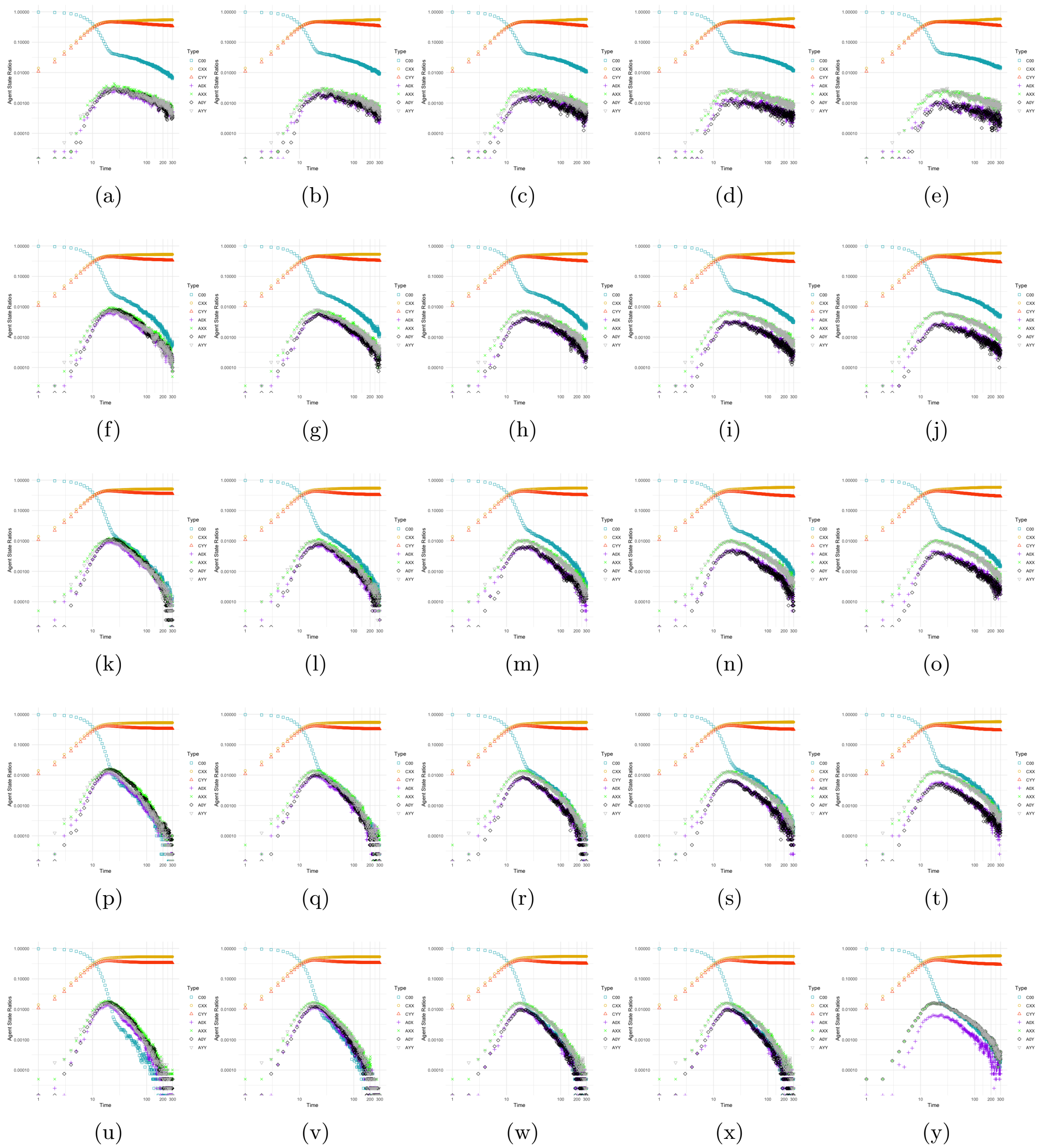
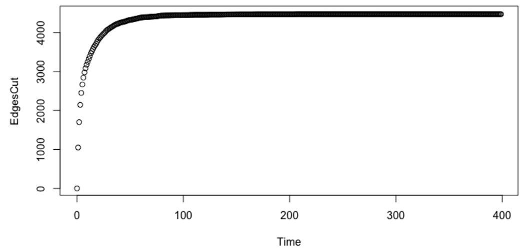


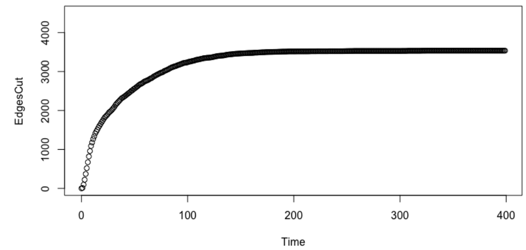
Figure 14: Full factorial design of parameters p_{agit} and p_{calm} in the grid-based model depicting agent state ratios for each combination.

The threshold of interactions resulting in disagreement is validated through variation of the cut-edge threshold γ. This involves four experiments, where $\gamma = \{0, 2, 4\}$ for the first three experiments, and is a uniform distribution between 0 and 4 for the final experiment.

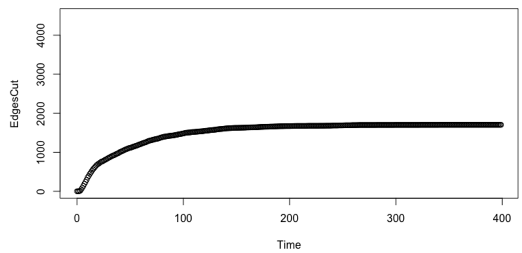
The number of cut edges over time for each experiment is shown in Figure 15, where the starting conditions are $p_{calm} = p_{agit} = 0.2$ for a randomly networked starting population of 5 000 agents with 8 connections on average. The proportion of agent E/I/O states are arbitrarily chosen as C00 = 0.10, CXX = 0.15, CYY = 0.30, AXX = 0.25, AYY = 0.10, A0X = 0.00, and A0Y = 0.1.



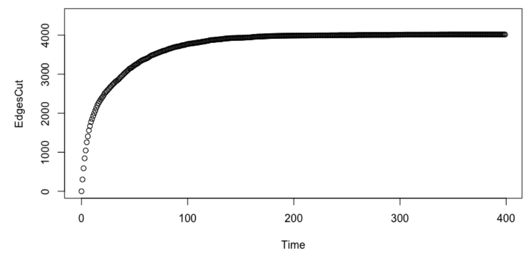
(a) $\gamma = 0$



(b) $\gamma = 2$



(c) $\gamma = 4$



(d) $\gamma =$uniform$(0, 4)$

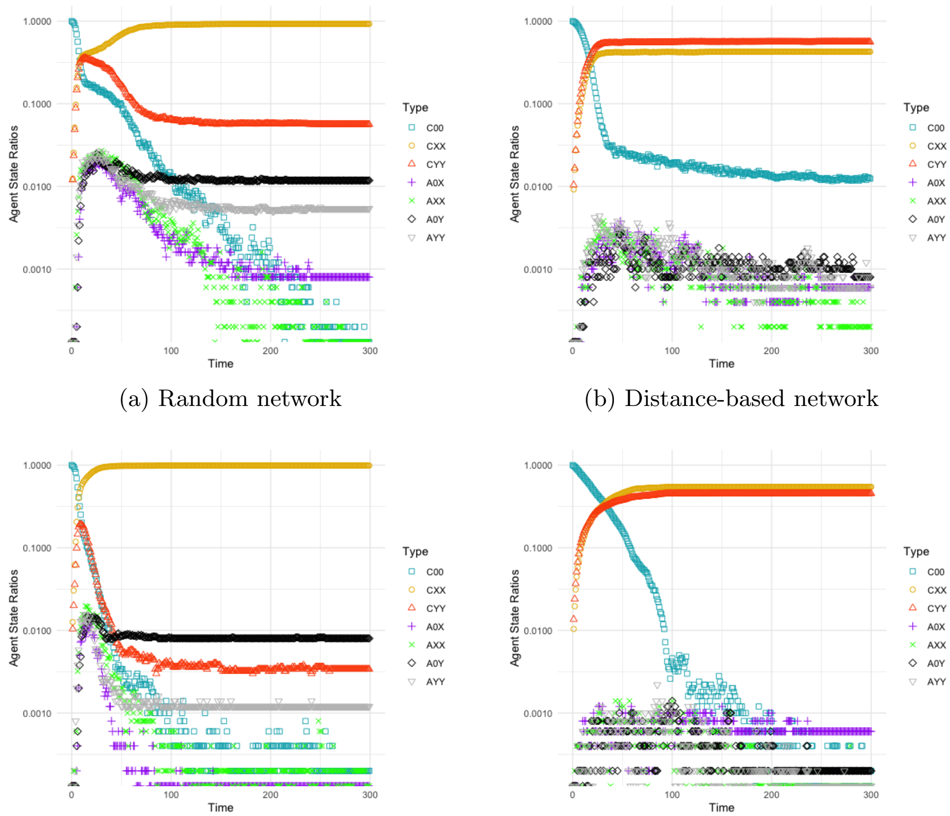
Figure 15: Number of cumulative edges cut over time for different cut-edge threshold values.

Each experiment, as shown in Figure 15, exhibits a similar shape, plateauing after a certain amount of time, with a greater threshold value resulting in a smaller number of total edges cut achieved after a certain period of time. A uniform distribution displays a similar curve shape to the definite threshold values, although it incorporates a stochastic aspect in that agents do not all exhibit the same threshold.

In addition to the cut-edge mechanism, the inclusion of various network types allow agents' neighbourhoods to be more realistically modelled in comparison to the gird-based structure. In a network, different agents can have mutual connections with some agents and not with others, which is more consistent with the description by Milgram [30] of the world as a social network. The size of an agent's network can also vary, mimicking an individual's connectedness or popularity which further adds to the stochastic nature of the model.

An experiment is performed to observe the range of effects that the network type has on the evolution of a certain population's E/I/O states. The four selected network types, namely random, distance-based, small world and ring-lattice networks, are applied to a population with the same starting conditions with a cut-edge threshold uniformly distributed between 0 and 4. The evolution of agent E/I/O state ratios until $t = 300$ is shown in Figure 16 using the logarithmic scale on the y-axis.

The selection of network type is seen to have a significant effect on the population, with varying degrees of metastability being achieved. For the random network, a large difference



(a) Random network

(b) Distance-based network

(c) Small world network

(d) Ring-lattice network

Figure 16: Agent state ratios for different network types.

between the majority and the minority is observed, with a larger proportion of the minority being in agitated states (A0Y and AYY). The proportion of calm, uninformed (C00) agents approaches zero.

For the distance-based network, a distance of 15 is chosen in a 500 × 400 × 15 environment. Metastability is quickly achieved with a small difference of support between the two parties and just over 1% of the agents being calm and neutral (C00). A similar level of support for each party is observed for the ring-lattice network, with the proportion of C00 agents diminishing slower at first, but then depleting altogether. The small-world network resulted in a rapid monopoly being formed with almost all agents being calm supporters of Party X.

The options available to the user in terms of network type allows another form of flexibility in potentially describing real-world data. A more accurate description of the development of real-world scenario could offer more predictive capability for the same situation.

5 Discussion

The proposed model describes a population of voter agents who hold a political opinion using knowledge and emotion as their control variables, similar to the model developed by Sobkowicz [27]. These variables are updated through interactions with other agents as well as political propaganda. The initial two-dimensional grid-based model is extended to a three-dimensional network model. This network-based model is further modelled to be dynamic with the inclusion of a cut-edge mechanism whereby connections between disagreeing agents can be severed under certain conditions concerning the intimacy of agent relationships. The extensions add more flexibility to the model which allow for a more realistic representation of reality. The different network types are shown to produce varying proportions of metastable agent states from identical starting conditions, which can be used to represent real political situations and predict future change.

In applying the model to a real-world data set, it is recommended that the user find a combination of parameters and network type that can accurately develop into a metastable state that represents a real-world scenario. Achieving a representation of past voter dynamics can validate specific parameters for predictive simulation. In-depth analysis of voter proportions, attitudes, and politcal campaigns are essential in achieving this. It must also be noted that the model would be best suited to simple political situations, as is the 2015 Polish case-study presented in Sobkowicz's study [23].

There are several avenues for future work which may stem from this research. The cut-edge mechanism may further be refined to consider the willingness of agents to form new connections with like-minded agents that are not yet within their social network. It is recommended that agents are given the ability to form connections with agents who share the same opinion, with a probability linked to the number of mutual connections the two agents hold. This would serve to replicate the higher likelihood of forming connections with individuals in mutual relationship circles, and possibly enable the development of more highly intra-connected groups. Other potential extensions may include allowing for more than two parties in the system, incorporating individual-based p_{agit} and p_{calm} values, the introduction and elimination of agents within the population, as well as the implementation of continuous values describing the E/I/O states.

References

[1] K. Kaye, "Data-driven targeting creates huge 2016 political ad shift: broadcast TV down 20%, cable and digital way up," 04 2017.

[2] A. Nadler, M. Crain, and J. Donovan, "Weaponizing the digital influence machine: The political perils of online ad tech," tech. rep., Data & Soceity Research Institute, 2018.

[3] A. Holst, "Big data market size revenue forecast worldwide from 2011 to 2027," 03 2020.

[4] A. Budzyn, "Data is the oil of the digital world. What if tech giants had to buy it from us?," 03 2019.

[5] A. Schomer, "Facebook's ad revenue growth slowed in Q2 - here's where its future growth will come from," 03 2019.

[6] F. J. Borgesius, J. Möller, S. Kruikemeier, R. Fathaigh, K. Irion, T. Dobber, B. Bodo, and C. De Vreese, "Online political microtargeting: Promises and threats for democracy," *Utrecht Law Review*, vol. 14, no. 1, pp. 82–96, 2018.

[7] J. Angwin, S. Mattu, and T. Parris, "Facebook doesn't tell users everything it really knows about them," 04 2016.

[8] S. Frenkel and C. Kang, "Facebook says Cambridge Analytica harvested data of up to 87 million users," 03 2018.

[9] Stamos, Alex, "An update on information operations on Facebook," 04 2017.

[10] United States of America vs. Internet Research Agency LLC *The United States District Court for the District of Columbia, [Legal Case]*, pp. 1–37, 2018.

[11] N. Penzenstadler, B. Heath, and J. Guynn, "We read every one of the 3,517 Facebook ads bought by Russians. Here's what we found," 04 2020.

[12] J. Allen and J. Abbruzzese, "Cambridge Analytica's effectiveness called into question despite alleged Facebook data harvesting," 03 2018.

[13] X. Song, C. Lin, B. L. Tseng, and M. Sun, "Modeling and predicting personal information dissemination behavior," in 11^{th} *ACM International Conference on Knowledge Discovery in Data Mining*, (Chicago (IL)), pp. 479–488, Association for Computing Machinery, 2005.

[14] E. Yaakobi and J. Goldenberg, "Social relationships and information dissemination in virtual social network systems: An attachment theory perspective," *Computers in Human Behavior*, vol. 38, pp. 127–135, 2014.

[15] J. T. Cox and D. Griffeath, "Diffusive clustering in the two dimensional voter model," *The Annals of Probability*, vol. 14, no. 2, pp. 347–370, 1986.

[16] E. Ben-Naim, L. Frachebourg, and P. L. Krapivsky, "Coarsening and persistence in the voter model," *Physical Review E*, vol. 53, no. 4, p. 3078, 1996.

[17] C. Castellano, S. Fortunato, and V. Loreto, "Statistical physics of social dynamics," *Reviews of Modern Physics*, vol. 81, no. 2, pp. 591–646, 2009.

[18] K. Sznajd-Weron and J. Sznajd, "Opinion evolution in closed community," *International Journal of Modern Physics C*, vol. 11, no. 6, pp. 1157–1165, 2000.

[19] R. Hegselmann and U. Krause, "Opinion dynamics and bounded confidence models, analysis, and simulation," *Journal of Artifical Societies and Social Simulation*, vol. 5, no. 3, p. 33, 2002.

[20] J. H. Fowler and O. Smirnov, "Dynamic parties and social turnout: An agent-based model," *American Journal of Sociology*, vol. 110, no. 4, pp. 1070–1094, 2005.

[21] C. R. Hunt, "When does redistricting matter? Changing conditions and their effects on voter turnout," *Electoral Studies*, vol. 54, pp. 128–138, 2018.

[22] E. Serrano, P. Moncada, M. Garijo, and C. A. Iglesias, “Evaluating social choice techniques into intelligent environments by agent based social simulation,” *Information Sciences*, vol. 286, pp. 102–124, 2014.

[23] P. Sobkowicz, “Quantitative agent based model of opinion dynamics: Polish elections of 2015,” *PLoS ONE*, vol. 11, no. 5, pp. 1–32, 2016.

[24] E. C. Zeeman, “Catastrophe theory,” *Scientific American*, vol. 234, no. 4, pp. 65–83, 1976.

[25] P. Sobkowicz, “Discrete model of opinion changes using knowledge and emotions as control variables,” *PLoS ONE*, vol. 7, no. 9, pp. 1–16, 2012.

[26] S. Abar, G. K. Theodoropoulos, P. Lemarinier, and G. M. O’Hare, “Agent based modelling and simulation tools: A review of the state-of-art software,” *Computer Science Review*, vol. 24, pp. 13–33, 2017.

[27] P. Sobkowicz, “Minority persistence in agent based model using information and emotional arousal as control variables,” *European Physical Journal B*, vol. 86, no. 7, pp. 1–11, 2013.

[28] P. Sobkowicz, “Effect of leader’s strategy on opinion formation in networked societies with local interactions,” *International Journal of Modern Physics C*, vol. 21, no. 6, pp. 839–852, 2010.

[29] A. Sutcliffe, R. Dunbar, J. Binder, and H. Arrow, “Relationships and the social brain: Integrating psychological and evolutionary perspectives,” *British Journal of Psychology*, vol. 103, no. 2, pp. 149–168, 2012.

[30] S. Milgram, “The small world problem,” *Psychology Today*, vol. 2, no. 1, pp. 60–67, 1967.