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Research Article

NORM SHIFTING: AN AGENT-BASED MODEL

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ABSTRACT

This paper aims to explain how norms change in the social world through agent-based modelling. Norms are rules, the roots of which lie in society to guide people to perform expected behaviours. Norms exist as sui generis in societies; however, they are improved and transformed by individuals in time. While norms are rather salient for some behaviours, they are subtle for others. The plurality of norms is one of the reasons for this ambiguity. Norm plurality occurs in societies where groups that have different norms for the same behaviour live together and interact constantly. Beyond that, norm differences are the basis on which different groups are defined. How do people change the norms that are already adopted, or how do adopted norms shift to opposite ones? This paper tries to explain norm shifts when there is more than one norm for a specific behaviour in an artificial society in accordance with certain factors: the minority/majority group's norm, group pressure, and loyalty of the individual. Agent-based modelling is a useful tool to understand the social world and create an artificial one. Agents shift their norms to interact with other agents. Results of the simulations show that minority or majority, group pressure, and loyalty are highly effective in norm shifting.
Keywords: Norms, agent-based modelling, minority group, group pressure, group polarization.

1. INTRODUCTION

Norms are particular standards of society or groups that regulate the way individuals behave. In social science literature, there are various but similar definitions of norms [1, 2], which present several concepts: normal, sanction, social control [3], obedience, conformity and compliance, social influence [4], learning, socialization, role, etc. There is an entrenched consensus about norms that says norms are common sense of acceptable behaviours.

Agent-based modelling (ABM) is a new and growing approach to modelling complex systems, especially in social sciences. Agents are autonomous, interacting software entities of a system [5, 6]. Agents behave through simple rules and are in interaction with other agents and the environment. Individual actions and their interactions in the actualities of the real world create a complexity that is modelled unequivocally by agent-based models [7]. Emergence of social phenomena in a macro-scale is the result of recurrent acts of agents and their interactions in a micro-scale.

ABM provides a remarkable test environment for normative behaviour researches [8, 9, 4, 10], such as social influence [11], norm learning [12], norm internalisation [13], norm

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transformation a nd transmission [14, 15, 16], and relationships [17]. Norm process (learning, adopting, changing, emergence) and social influence are studied in social simulation together or separately [18, 19].

In this paper, norm change affected under social influence (group pressure) and from minority/majority influence is examined by an agent-based simulation. The simulation model determines how norms operate in an intra-agent process and how norms are transmitted in an inter-agent relationship in society where different groups and conflicting norms exist simultaneously. The model also exhibits the norm shifting of an agent between two conflicting group norms.

2. THEORETICAL BACKGROUND AND LITERATURE

2.1. Norms in the Literature

Norms are social facts, and norm learning is a social process. People learn the rules, operations, and norms that belong to the society in which people are born. People not only obey to avoid punishment or to get a reward explicitly, but also follow norms mostly without thinking, since most norms are internalised by people and guide them in their daily life implicitly [13]. Norms provide people a comfort zone and time. This function of norms facilitates people's lives [3] and shortens the time they use to think how to behave [14, 20].

According to Cooley [21], primary groups (family, peers, close friends, and neighbours, who are in intimate, face-to-face association and cooperation) are dominant in socialisation. Therefore, a primary group is crucial to define a person's initial norms. In family and peer groups, people learn how to eat, get dressed, and communicate with other people — in short, how to behave. Secondary groups consist of more people, such as friends, colleagues, union members, and politicians, who have weak or no link with each other. Sutcliffe and Dunbar's studies state that there are four separate layers of relationships. The two innermost layers are the support clique with approximately five members and the sympathy group with 15 members. The last two layers are the affinity group of 50 individuals and the active group of 150 individuals. Each layer is included in the next layer, which has more members [22, 23].

In the earliest studies, Sherif's [24], Asch's [25], and Milgram et al.'s [26] experiments reveal the emergence of norms and show how group size and concurrence affect a group's judgment. These classic experimental studies conceptualised behaviours into conformity, obedience, and compliance, which are acted with norms, group pressure, and social influence [1]. Latané's Social Impact Theory [27] and Moscovici's minority studies [28, 29] disclose social change and alteration of a group's norms afterwards. These studies show how norm mechanisms operate, such as norm emergence, spreading, enforcement or changing by social influence, or belonging to a minority/majority.

Researchers delineate different norm types, such as social norm, moral norm, cultural norm, personal norm, and subjective norm [30, 31]. Cialdini et al. [32] suggested a significant distinction among norm types as descriptive norms (what most others do) and injunctive norms (what most others approve or disapprove). Injunctive and descriptive norms on a behaviour are mostly congruent [33], but a specific behaviour can be regarded as an injunctively normative and descriptively non-normative one, or vice versa [3].

Even if norms regulate people's social life and make certain behaviours come naturally and help them assume others' actions, norms are not salient for everyone or every time. For example, children are not aware of most norms because they are in the learning process, and immigrants cannot be expected to know cultural norms in their new country. Sometimes the reason for ambiguity is the existence of more than one norm about the same subject, like in organ donation or counterfeit consumption subjects. People approving or disapproving of these issues can exist in the same society and time period. Usually, more than one norm on the same behaviour can be discernible in a society with a lot of different ethnic groups that have different cultural norms that share the same public sphere. In discerning different groups in a society, norms provide a fundamental reference point.

2.2. Norms in Agent-based Modelling

Agent-based modelling (ABM) is a computational method in which artificial entities interact each other as well as their environment over time [5, 9, 34, 35]. The roots of ABM originate from game theory and cellular automata which belong to computer science field [36, 37]. Schelling's "Segregation Model" developed in 1970s is one of the pioneer studies that uses ABM in social science [36, 38] and another example is Axelrod's "The Evolution of Cooperation" [18, 37] which is developed in 1980s. Simulation is known as "third symbol system" in social science following natural language and mathematics which hold the first and second place, respectively [36, 39]. Similarly, it is accepted "generative" as the third approach after "inductive" and "deductive" sciences [34]. Social patterns, structure and behaviors are not explicitly programmed; social phenomena emerge at macro level from the agent's behaviors and interactions at micro level [5, 6, 34, 37]. ABM is useful tool to understand and interpret of complex system and system behavior especially in social complexity. Thus, ABM assures a safe environment for some impossible and/or unethical experiments conducted by artificial societies [5, 37].

In the ABM literature, norms regulate behaviours explicitly or implicitly. Researchers from different backgrounds or with different working purposes bring about alternative norm definitions, norm functions, or processes [1, 10]. Also, some researchers explicitly base their assumptions on a theory in social sciences, while others do not [15, 40].

Two research fields come into prominence in studies: normative process and social network [16, 41, 42, 43]. Norm emergence, generated by game theory and based mostly on Axelrod's [18] evolution of cooperation, is a huge part of studies on normative processes. Agents play a prisoner's dilemma, choosing between the two actions of cooperating/defecting or punishing/not punishing based on the boldness and vengefulness parameters of their strategy. This study shows how cooperation can emerge and evolve as a norm in a society of selfish agents. In Verhagen's [12] study, group decision emerges as a norm that is part of an agent's decision-making process, which involves consuming food A or B or moving or doing nothing as alternatives. Agents make a choice with their own personal evaluations or obey the group decision. Verhagen reports that higher agent autonomy caused a decrease in the predictability of behaviour. There is a lack of or inadequacy in researches on co-existing or competing norms [41].

Defining relationships between agents and identifying social influence on an agent network are based on agent world topologies. Two main network types are 2-D lattices and complex networks (scale-free and small world) where agents are stationary or mobile. Alam et al. [44] have given this division as physical and social space. Topology and mobility determine that agent's neighbourhood and relations are stationary or dynamic. Agents in Schelling's Segregation Model, which is one of the first and most known models in ABM history in social sciences, move to new empty locations, if agents who are from one of two groups in the model feel themselves to be a minority in their current location [38]. In time, agents form groups with their fellows depending on their local positions.

In Epstein's [14] model, two norm types exist. Agents are settled on a ring and agents update their norms searching their radii (neighbours), which are updated parallel to the previous result of norm changing. Norm changing is determined by the majority of the neighbours' norms. Epstein studied local conformity, global diversity, and punctuated equilibria. This study is based on two types of norms and physical network. The simulation results are similar to Social Impact Theory [19]. In this paper, each cell in the 40x40 matrix has an opinion of one of two options, and the majority of opinions dominates this matrix in almost every run or parameter change. The minority can survive only at the edge of the matrix, where individuals' surrounding circle contains a less opposite opinion. Muldoon et al.'s [20] model studied ovation behaviour in a theatre. Their model combined intrinsic preference and extrinsic propensity (norms) with different weights as a result of which norms emerge. Agents can see either the entire audience or only some of them (within a cone of 30º) in different simulation scenarios.

Although a simulation study accepted that norm is a continuous variable in system dynamic models [45], all agent-based studies mentioned above admit implicitly or explicitly that norms are discrete. In these ABM studies, agents are able to change their norms in two consecutive steps of simulation, which does not to match with the real world. In this agent-based study, norm is considered as a continuous variable.

Moreover, norms are not salient, overt, or monolithic inevitably. In fact, norms are not singular in most situations, especially for children and immigrants. There is norm plurality, and some norms even contradict each other in the real world. But these contradictions are not perpetual. People learn new norms without having one or change their norms to a new one. This learning or change does not occur instantly. In these ABM studies, agents are able to change their norms in two consecutive steps of simulation, which does not to match with the real world. In this agent-based study, norm is considered as a continuous variable. It is the output of an interaction process that is named 'norm shifting' and examined in this paper.

3. AN AGENT-BASED CONCEPTUAL MODEL

In this model, norm is defined as a bipolar and continuous variable between 0 and 1. Two poles of the variable represent two opposite norms on a behavior. The mid-point of the variable (0.5) is a threshold that separates society into two norm groups: Group A and Group B. Norm salience is high on poles where norm is injunctive; from poles to centre where norm is descriptive, it becomes ambiguous (see Fig. 1). Near the poles, norm strength is high and norms are injunctive. Norm strength decreases and norms turn into descriptive ones towards the centre. Around 0.5, norms are fuzzy. An agent x with a norm value of 0.52 and agent y with a norm value of 0.46 do not have exactly different thoughts, beliefs, or ideas about issue. However, 0.5 is the threshold to determine group identity. Therefore, agent x is a member of Group B, while agent y is a member of Group A.

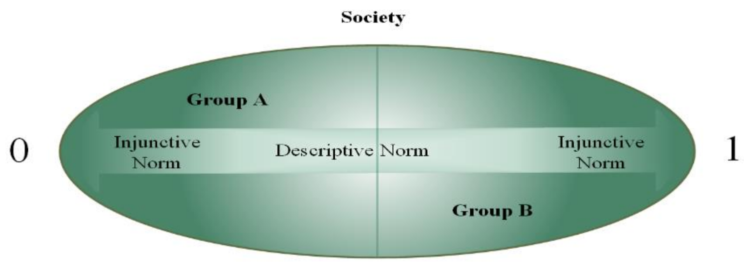

Figure 1. Bipolar norms

Agents have two types of relation: close circle and distant circle. An agent x has immediate, face-to-face relations (families, close friends, peers, and neighbours, etc.) with close circle agents who are from the same group as agent x. Also, a close connection is reciprocal. If agent x is in agent y's close circle, agent y is also in agent x's close circle. The members of the close circle for every agent are assigned randomly from the agent's own group.

A distant circle consists of secondary contacts and the members of the distant circle of an agent are assigned randomly from the whole society. The relations of these agents are more formal. It is even possible that some agents in agent x's distant circle who are celebrities, business people, political or religious figures, or a boss do not know agent x. Thus, the distant circle relation is not reciprocal for the agent.

3.1. Norm Update Rule

In the model, society consists of two groups: Group A and Group B. An agent's norm is generated randomly in accordance with the agent's group; Group A (G^A) contains agents whose norm is between group norm limits $(0, 0.5)$, while Group B (G^B) contains agents whose norm is between group norm limits $(0.5, 1)$. In each iteration, the agent calculates its own norm in accordance with the norms of other agents who are in its close and distant circles. In every iteration, norm is recalculated to live in conformity within the environment. The algorithm is explained in detail below.

N_{it} is norm, and C_{it} is the set of agents in the close circle of agent i at time t; $C_{it} = C_{it}^{+} \cup C_{it}^{-}$,

$$C_{it}^{+} = \{j | N_{jt} \geq 0.5 \ and \ j \in C_{it}\} \tag{1}$$

is the subset of the close circle whose members' norm is equal to or greater than 0.5, and

$$C_{it}^{-} = \{j | N_{jt} < 0.5 \ and \ j \in C_{it}\} \tag{2}$$

is the subset of the close circle whose members' norm is smaller than 0.5. D_{it} is the set of agents in the distant circle of agent i at time t; $D_{it} = D_{it}^{+} \cup D_{it}^{-}$,

$$D_{it}^{+} = \{j | N_{jt} \geq 0.5 \ and \ j \in D_{it}\} \tag{3}$$

is the subset of the distant circle whose members' norm is equal to or greater than 0.5, and

$$D_{it}^{-} = \{j | N_{jt} < 0.5 \ and \ j \in D_{it}\} \tag{4}$$

is the subset of the distant circle whose members' norm is smaller than 0.5.

Secondly, agent i checks every neighbor's (agent j) norm's difference from the threshold (0.5) as follows:

$$N_{it}^{C^{+}} = \sum_{j \in C_{it}^{+}} (N_{jt} - 0.5) \tag{5}$$

is the sum of close circle members, whose norm is equal to or greater than 0.5, and the difference from threshold agent j at time t.

$$N_{it}^{C^{-}} = \sum_{j \in C_{it}^{-}} (0.5 - N_{jt}) \tag{6}$$

is the sum of close circle members, whose norm is smaller than 0.5, and the difference from threshold agent j at time t, and it is likewise

$$N_{it}^{D^{+}} = \sum_{j \in D_{it}^{+}} (N_{jt} - 0.5) \tag{7}$$

is the sum of distant circle members, whose norm is equal to or greater than 0.5, and the difference from threshold agent j at time t.

$$N_{it}^{D^{-}} = \sum_{j \in D_{it}^{-}} (0.5 - N_{jt}) \tag{8}$$

is the sum of distant circle members, whose norm is smaller than 0.5, and the difference from threshold agent j at time t. The high sums of differences of an agent mean that the agent's small groups (close and distant circles) have high norm salience. It implies that the agent is subjected to high pressure by these circles. Even so, the circle that the agent will obey depends on the importance levels of the circles.

To calculate total positive and negative difference, a weighted sum of close and distant circle norm differences is used.

μ_C is close circle weight, μ_D is distant circle weight, and $\mu_C + \mu_D = 1$.

$$N_{it}^{+} = (\mu_C * N_{it}^{C^{+}}) + (\mu_D * N_{it}^{D^{+}}) \tag{9}$$

is the weighted sum of neighbor agents whose norm is equal to or greater than 0.5. Likewise,

$$N_{it}^{-} = (\mu_C * N_{it}^{C^-}) + (\mu_D * N_{it}^{D^-}) \quad (10)$$

is the weighted sum of neighbor agents whose norm is smaller than 0.5.

The change of the norm of agent i at time t is defined as the product of norm exposure α_{it} and a constant θ. Norm exposure is defined as a table function depending on the norm ratio, which is the proportion of minimum total norm difference and maximum total norm difference for agent i.

$$\text{Norm ratio for agent } i = \frac{\min(N_{it}^{-}, N_{it}^{+})}{\max(N_{it}^{-}, N_{it}^{+})} \quad (11)$$

Using the norm ratio function, we calculated α_{it}. The bigger the gap between two sums, the more powerful the effect of the norm will be. Agent i perceives the dominant norm direction better. As the gap between sums grows, the pressure in the direction of a bigger sum increases, and agent i's perception is mainly under social norm exposure.

Norm exposure is a non-linear function within lower and upper bound linear function (Fig. 2). When the norm ratio is equal to 1, the agent perceives equal effect in both directions and the norm of the agent does not change. Therefore, lower and upper bound function must pass through (1, 0) point. If the norm ratio is about 0, the total norm difference in a certain direction dominates and the agent increases its norm by the maximum possible value in this direction. As the norm ratio increases, the norm exposure function approaches the lower bound linear function.

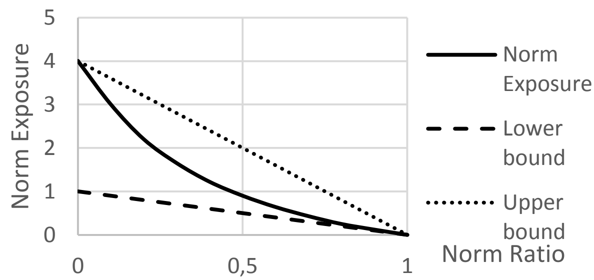

Figure 2. Norm exposure table

$$\Delta N_{it} = \begin{cases} \theta\alpha_{it} & \text{if } N_{it}^{+} > N_{it}^{-} \\ -\theta\alpha_{it} & \text{if } N_{it}^{+} < N_{it}^{-} \end{cases} \quad (12)$$

θ is a constant that gives the amount of norm change when the norm ratio is close to 0.5. Norm exposure (α_{it}) is a multiplier that determines the rate of change of norm at time t, and ΔN_{it} is the amount of change of agent i's norm at time t. Agent i adjusts its own norm depending on neighbours and updates the norm in the dominant direction and exposure value by using Eq. 13.

$$N_{it} = N_{i(t-1)} + \Delta N_{it} \quad (13)$$

3.2. Group Norm

'Remainder' is the agent whose last norm value remains in the limits of its group. The set of remainders is

$$R_t^A = \{j \mid 0 \le N_{jt} < 0.5 \; and \; j \in G^A\} \quad (14)$$

for Group A and

$$R_t^B = \{j \mid 0.5 \le N_{jt} \le 1 \; and \; j \in G^B\} \quad (15)$$

for Group B.

'Shifter' is the agent whose last norm value extends the limits of its group. The set of shifters is

$$S_t^A = \{j \big| 0.5 \le N_{jt} \le 1 \; and \; j \in G^A\} \quad (16)$$

for Group A and

$$S_t^B = \{j \big| 0 \le N_{jt} < 0.5 \; and \; j \in G^B\} \quad (17)$$

for Group B.

In the model, agents are not mobile. Agents update their norm in each step, and their norms may not remain in the limits of their groups in time. But agents do not change their group belonging. Hereby, the group's size is fixed.

Group norm is defined as the average of its members' norm at time t:

$$\sum_{j \in G^k} N_{jt} / \big|G^k\big|, k \in \{A, B\} \quad (18)$$

where $|G|$ represents the size of set G.

4. EXPERIMENTAL STUDY

4.1. Experimental Design

The simulation is modelled in AnyLogic 7.3.5. Personal Learning Edition. Simulation results are compiled by Excel.

The population is 10,000 agents, and every agent is initially created as a member of Group A or B. The agent has a random norm value within the group's norm limits, which are (0, 0.5) for Group A and (0.5, 1) for Group B. Every agent's close circle has 50 members who are selected randomly from the agent's group. The agent has primary and reciprocal relations with every agent in its close circle. And every agent has secondary relations with 100 agents who are selected randomly from the whole society. The agent has reciprocal relations with agents in the distant circle by 40% chance. Every agent has 150 connections with other agents in total.

The model has two parameters: the rate of Group A and the close circle weight. The Group A rate is the percentage of the Group A population in the whole society. Group populations are calculated relative to the Group A rate initially.

Table 1. Model parameters

Parameters									
Group A ratio	10%	20%	30%	40%	50%	60%	70%	80%	90%
Close circle weight	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9

The sum of the close circle weight (μ_C) and distant circle weight (μ_D) is equal to 1. If the close circle weight is 0, the agent updates its own norm only considering the agents in the distant circle, which contains agents from the whole society. On the contrary, when the close circle weight is 1, the agent updates its norm by just the close circle, whose members are from the agent's own group, and thus the agent ignores the other norm group.

In simulation, both parameters change for 0.1 unit gradually. There are nine values for rate (from 10% to 90%) and nine values for circles weight (from 0.1 to 0.9); in total, there are 81 different scenarios. The results of 0 and 1 values of both parameter results are predictable, so they are ignored. Replication length is 100 steps, and the number of replications is 50 for each scenario.

4.2. Simulation Results

4.2.1. Agent's Norm Shifting

Table A1 gives the average remainder size of Group A at the end of the simulation, and Figure 3 gives the change of average percentage of remainder in time. (Both groups have similar results, so simulation results are interpreted only for Group A.)

When the rate is 10%, Group A has 1,000 agents, and all agents are remainders initially. At the end of step 10, ~71% of the group's population of Group A are remainders (~713 agents), and ~29% of the group's population of Group A are shifters (~287 agents) when the close circle is 0.1 (Table A1). Additionally, ~35% of Group A are remainders (~346 agents), and ~65% of Group A are shifters (~654 agents) at the end of the 20th step. The remainder percentage decrease continues among the following steps. At the end of the 30th step, one or two remainder agents are left in Group A. After the 31st step, all agents in Group A have a norm bigger than a 0.5 value, so no remainder is left in Group A.

On the other hand, the percentage of shifter decreases when the group's rate increases (Figure 3). When the rate is 20% and the close circle weight is 0.1, Group A has 2,000 agents, and all agents are remainders initially. At the end of the 10th step, ~79% of the group's population of Group A are remainders, and Group A has ~21% of the group's population as shifters. When rates are 30%, 40%, and 50%, the remainder percentages are ~89%, ~95%, and ~100%, respectively, at the end of step 10. After steps, remainder percentages are ~49% (rate is 20%), ~67% (rate is 30%), ~87% (rate is 40%), and ~99% (rate is 50%). After the 30th step, remainder percentages are ~11% (rate is 20%), ~36% (rate is 30%), ~72% (rate is 40%), and ~99% (rate is 50%).

The percentage of remainders continues to decrease in the following steps, but the decreasing rate of the percentage of remainders reduces. When the rate is 60%, although some agents have a norm that is out of their own group limit in the early steps of a few simulation runs, those agents quickly return to their group limit. When the rate is higher than 60%, Group A keeps all of its members as remainders from the beginning of the simulation. Furthermore, agents of Group B shift their norm into Group A's limit, since Group B has a low rate (below 40%). These results overlap Nowak et al.'s [19] study on Social Impact Theory. If a group is a majority, society loses its heterogeneity and becomes more homogenous. The majority group's norm dominates the whole society.

By the same token, when the close circle weight is 0.2 and the rate is 10%, ~75% of the group's population of Group A are remainders (~755 agents), and Group A has ~25% of the group's population as shifters (~245 agents) after step 10. The remainder percentage rises to ~81%, ~86%, ~91%, and ~97% for 0.3, 0.4, 0.5, and 0.6 close circle weight, respectively. When the close circle weight is 0.7, the change in percentage of remainders is very small in the first 10 steps (~99%), but there is almost no remainder left at the end of 100 steps.

The norm of all agents of Group A is bigger than 0.5 at the end of the simulation run for low and medium close circle weights. When the close circle weight is 0.1, there is no remainder in Group A at the 32nd step (rate is 10%). When the close circle weight is between 0.2 and 0.6, the number of steps required for all agents in Group A to shift their norm is 34, 37, 42, 49, and 63, respectively. If the close circle weight is 0.7, there are always remaining agents in Group A in step 100. When the close circle weight is 0.8 and 0.9, no agent has a norm bigger than 0.5 in any step from the beginning. High close circle weights cause groups to keep their members as remainders from the beginning. Similarly, for a high rate (>60%), there is no shifter in any step from the beginning of the replication. If the rate is 60%, there are a few shifters in the early steps for close circle weights of 0.1 and 0.2. If the rate is 50% and the close circle weight is above 0.5, there is no shifter in any step. For a rate of 40%, the close circle weight in which all agents remain in their groups is 0.6. All agents are remainders from the beginning to the end of 100 steps, when the close circle weight is 0.7 and the rate is 30%.

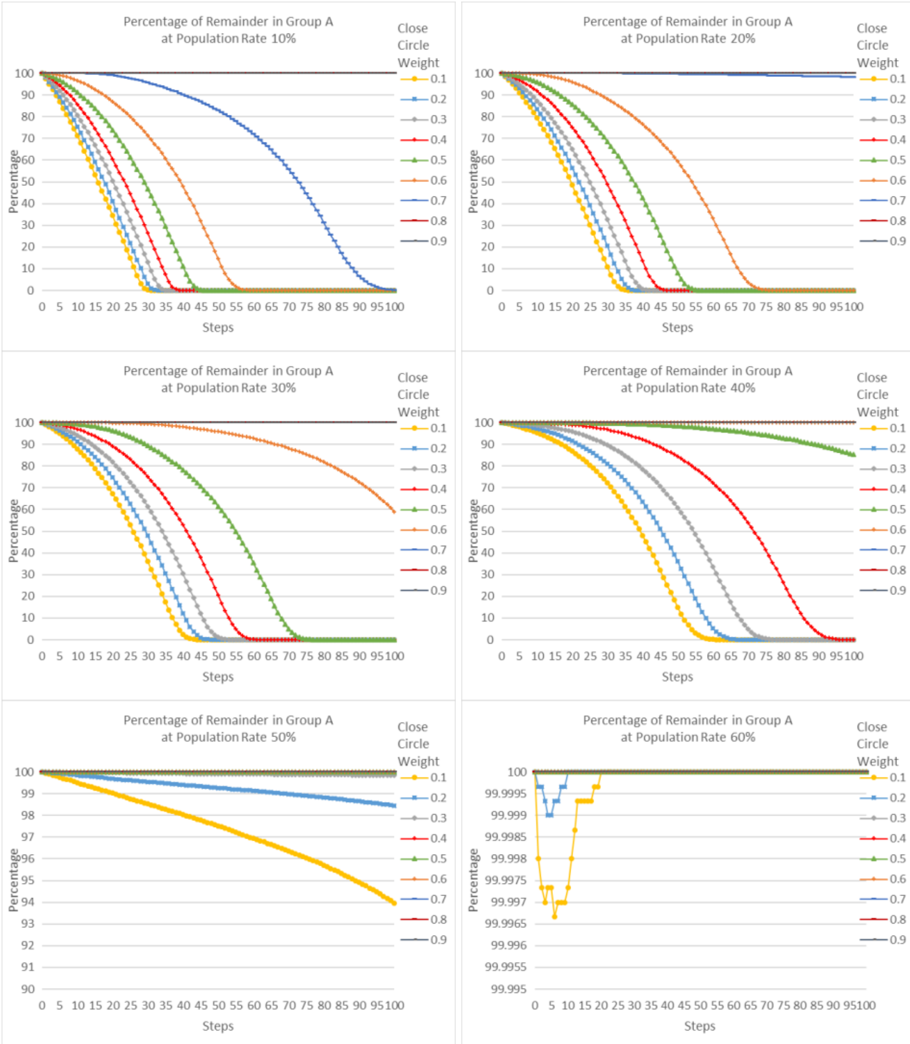

Figure 3. Percentage of remainders in Group A

When the rate is 40% and the close circle weight is between 0.1 and 0.6, all agents turn to shifters in 100 steps. If the close circle weight is 0.7, shifters emerge from 14th step in the simulation, and the number of shifters increases gradually. When the close circle weight is 0.8 and above, there is no shifter in any step at any rate. These results are different from Nowak's study, such that population rate or being a majority does not have a significant effect on norm changing behaviour when the close circle weight is very high. Strong close circle ties or high close circle pressure (or high loyalty) assures that groups keep their members as remainders. It shows that small groups can survive in the real world. As group pressure gets higher or group identity gains importance, changing norms becomes harder.

4.2.2. Group Norm

The aim of this experiment is to understand how group norms change each year and how groups' population rate and close circle weight affect group norms.

In the beginning of the replications, each agent in Group A and Group B is randomly assigned a norm between its own group norm limits. The group norm is the average of the members' norm. So, Group A norm is about 0.25 and Group B norm is about 0.75 in the beginning. Figure 4 gives the change of the norm of Group A and Group B during the simulation steps for each close circle weight and population rate. The results are symmetric around the 0.5 threshold for Group A and Group B.

Figure 4 shows that when the rate is 10%, Group A norm reaches the maximum between the 54th step and the 80th step for different close circle weights (0.1–0.6). Low and medium close circle weights (0.1–0.6) show that the remainder agents in Group A transform to shifters in the following steps, and the group norm goes to 1. When the close circle is 0.7, although Group A norm decreases in early steps, it starts to increase after the 13th step. When the close circle is 0.8 or 0.9, the group norm decreases to 0 from the beginning of the replication. When the group population is half of society, Group A norm decreases from the beginning for each close circle weight and goes to 0. It reaches 0 at the 97th, 59th, and 44th steps when the close circle weight is 0.7, 0.8, and 0.9, respectively.

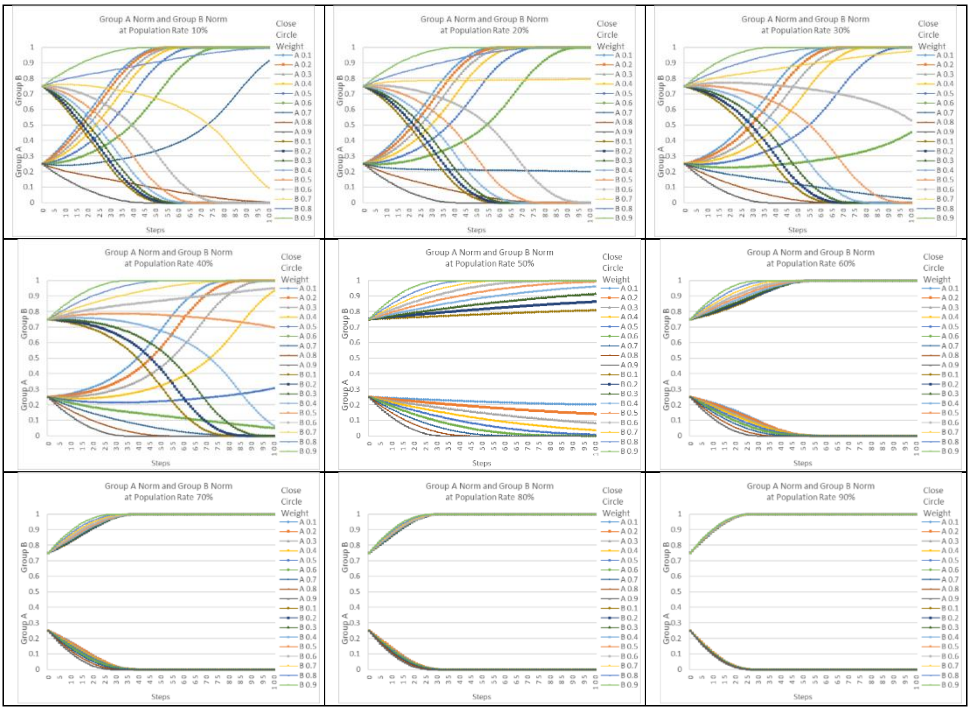

Figure 4. Group average norms

When the group population is 60% and above, the group norm reaches 0 for all close circle weights. If the group is a majority (above 60%), the group norm converges to the group's extreme point, and group polarisation always occurs.

Figure 5 shows that when the group population is below 50%, groups cannot keep their members as remainders. Social polarization actualises, and the society's average norm goes to the majority group's extreme point (0 for Group A and 1 for Group B) at low close circle weights.

With high close weights, the agent is under high pressure to go to its own group, so group polarisation actualises, and the group average norm goes to its extreme point. However, society's norm does not converge to extreme points if the close circle weight is high enough. A high close circle causes that minority group to keep its members as remainders, and so the minority norm survives. Hence, society's norm does not reach extreme points.

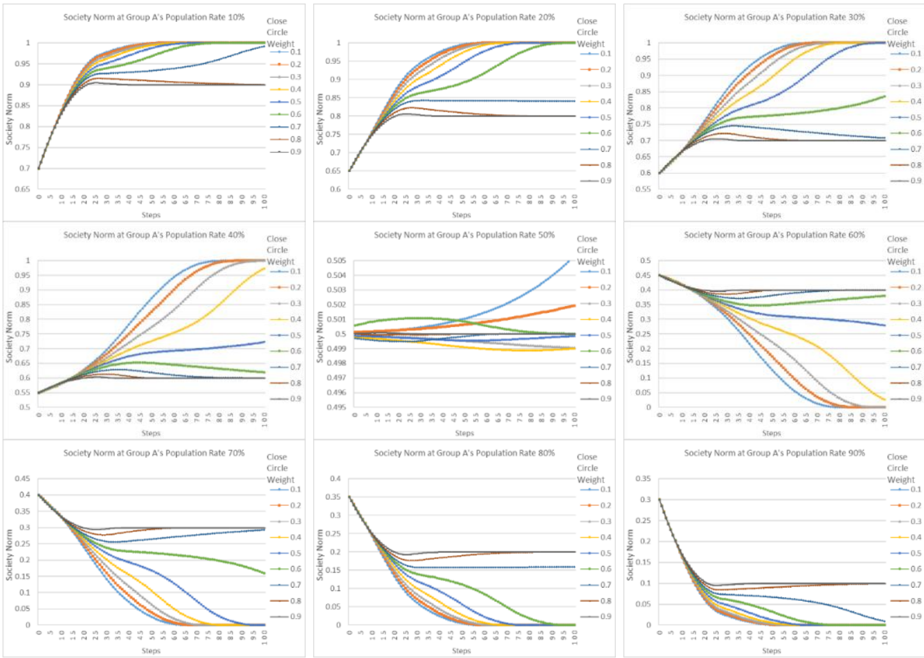

Figure 5. Society's average norm

4.2.3. Close Circle Size Effect

In the previous experiment, close circle size is 50 agents and distant circle size 100 agents. The experiments are repeated for 5, 15, 25, 50 and 75 agents in close circle when total network is 150 agents [46, 47, 48]. Replication length is 100 steps, and the number of replications is 10 for each one of the close circle sizes.

Figure 6 displays that while close circle size decreases to 5 agents and group population is below 50%, minorities disappear in 100 steps for all close circle weights. When close circle consists of 15 agents and group populations are below 10% and 20%, it is again observed that minorities are vanishing in 100 steps and long term. If group population is above 30% then the strong close circle ties (close circle weight is 0.9) ensure to keep group surviving.

When close circle consists of 25 agents and close circle weight is 0.9, minorities can survive for all group populations. Also, while group population is increasing, minority group keeps its members as remainder. If minority group population is 30% then the group can survive in 100 steps when close circle weights are 0.8 and 0.9.

When close circle consists of 75 agents, distant circle has exactly same amount of 75 agents. If minority group population is 10% then minority group keeps its members as remainder when close circle weight is 0.6 or above. If minority group population is 30% then lower limit of close circle weight for surviving in 100 steps is 0.5.

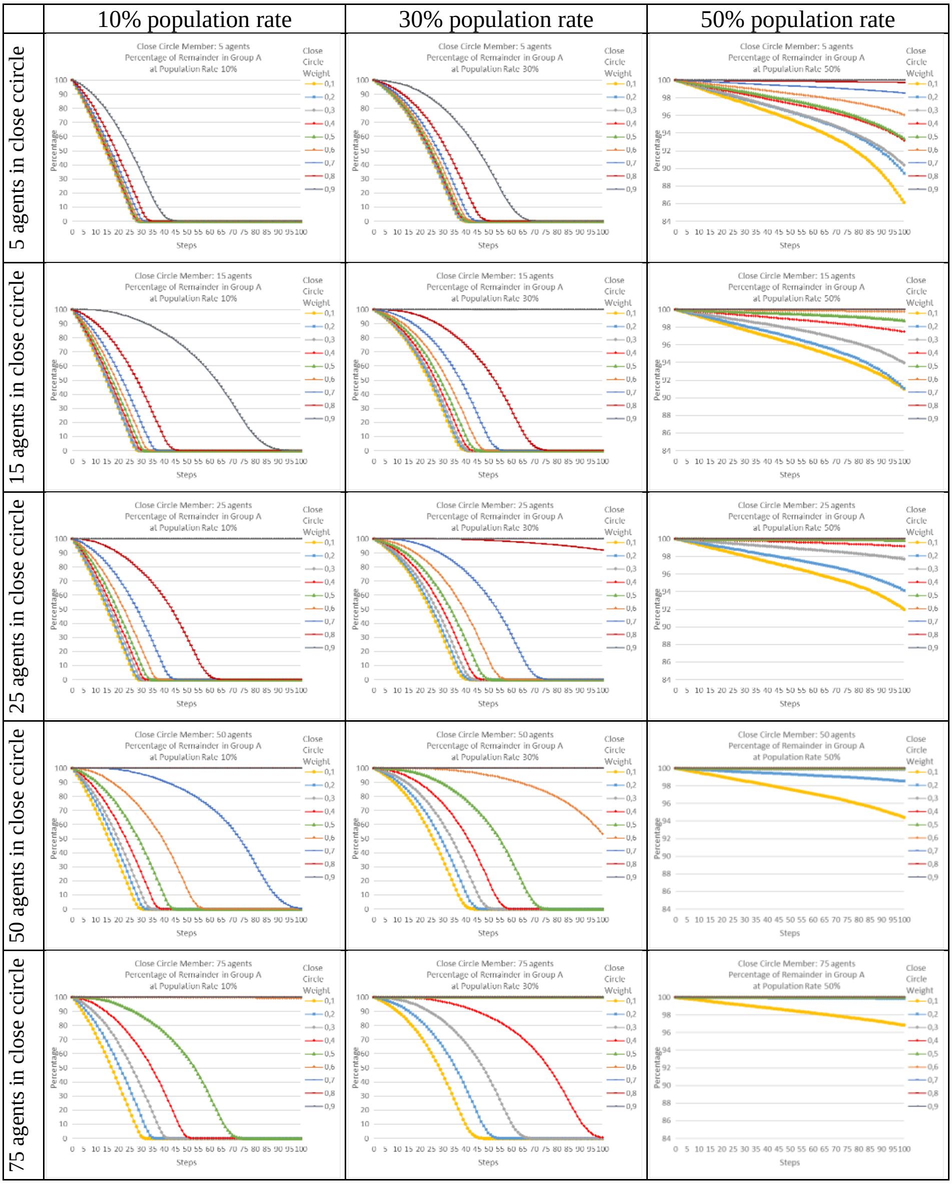

Figure 6. Percentage of remainders in Group A for different close circle size

When minority group population is %10, minority group norm vanishes about 30th step for each one of the close circle sizes. This shows close circle size does not have effect on norm vanishing step. Furthermore, when minority group population is 30%, minority group norm vanishes about 40th step. When close circle size is below 25 agents, percentage of remainder's curves are closer each other for low close circle weights. On the other hand, when close circle size are 50 agents and 75 agents, curves dramatically separate each other. Group norms vanishes at higher steps for low close circle weights and group norms survive for high close circle weights in 100 steps.

5. DISCUSSION AND LIMITATION

Agent-based modelling offers a novel way to model complex systems, especially artificial societies. Also it is convenient option to test environment for social experiments. Real-world like developed and improved norm mechanisms based on social theories in artificial societies provide much more realistic social models and simulations.

In this paper, we try to show norm shifting in society by two dimensions: population rate (majority/minority) and close circle weight (group pressure/loyalty). Obviously, keeping group members and sustaining group norm are easy in majority or in relatively large minorities. Group population rate in the society is an important factor to keep group norms. While population of minorities is increasing, the number of people who have the norms of minorities increases; thus, minorities and their norms survive in the society. If population of minorities have is small then group ties become crucial: the stronger it is, the higher the chance of survival of them and their norms. If a minority group has strong group ties and the group members can socialize at least 15 members of his/her group frequently then the group can survive despite having small population in the society.

Being a majority in a society is essential to keep group members in the group and to retain the group norm. Majority group always keeps its norms and it also affects minority group members. However, close circle weight is also a substantial factor to group norm survival. Simulation results show that small groups can withstand the majority pressure and keep their own norm throughout the years by high group pressure or loyalty. Having different norms in a society precludes polarization at one side or opinion. The majority group or norm surpasses others in time, but minorities can prevent it or at least slow it down.

This paper accepted that a specific behaviour has two opposite norms — should or shouldn't — and individuals have norms between these two poles. In the real world, this is not valid for every behaviour, and most behaviours do not have two opposite directions. More than one norm about the same behaviours usually involves cultural norms. The norm shifting model can offer an insight into social change and adaptation for minorities, especially immigrants.

Real-world minorities, especially ethnic groups, have high group pressure and/or loyalty. Pressure or loyalty is not about a specific behaviour, but about protecting group identity. Ethnic groups preserve a norm collection that may cover marriage, education, relations, child treatment, dressing, and a lot of cultural norms. Similarly, simulation results show that minority groups that have high group pressure or whose members have high loyalty can survive even if they have a very small population rate.

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Appendix

Table A1. Number of remainders in Group A for each population rate and close circle weight in decades

Pop. Rate	Step	Close Circle Weight 0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
10%	0	1000	1000	1000	1000	1000	1000	1000	1000	1000
	10	712.96	754.7	808.84	858.12	912.74	967.3	999.54	1000	1000
	20	346.24	411.26	506.28	605.44	739.04	870.72	989.98	1000	1000
	30	1.68	30.56	129.44	264.86	468.08	712.84	956.56	1000	1000
	40	0	0	0	0.2	110.88	479.14	901.94	1000	1000
	50	0	0	0	0	0	145.7	827.9	1000	1000
	60	0	0	0	0	0	0.26	719.14	1000	1000
	70	0	0	0	0	0	0	558.28	1000	1000
	80	0	0	0	0	0	0	313.06	1000	1000
	90	0	0	0	0	0	0	66.28	1000	1000
	100	0	0	0	0	0	0	0.92	1000	1000
20%	0	2000	2000	2000	2000	2000	2000	2000	2000	2000
	10	1588.66	1671.24	1747.96	1835.94	1920.12	1989.18	2000	2000	2000
	20	973.2	1128.74	1300.86	1504.52	1714.5	1919.08	1999.9	2000	2000
	30	216.76	408.42	651.94	980.86	1372.94	1764.2	1999.1	2000	2000
	40	0	0	13.94	274.3	855.6	1532.88	1996.3	2000	2000
	50	0	0	0	0	161.5	1187.96	1991.9	2000	2000
	60	0	0	0	0	0	663.96	1987.8	2000	2000
	70	0	0	0	0	0	77	1982.2	2000	2000
	80	0	0	0	0	0	0	1976.7	2000	2000
	90	0	0	0	0	0	0	1970.4	2000	2000
	100	0	0	0	0	0	0	1964.3	2000	2000
30%	0	3000	3000	3000	3000	3000	3000	3000	3000	3000
	10	2641.52	2737.78	2822.88	2910.7	2982.48	2999.76	3000	3000	3000
	20	2021.22	2239.9	2455.12	2676.56	2892.3	2996.78	3000	3000	3000
	30	1085.58	1436.84	1841.84	2254.22	2685.88	2981.24	3000	3000	3000
	40	76.22	368.7	913.26	1588.14	2349.64	2942.78	3000	3000	3000
	50	0	0.12	34.22	613.82	1845.36	2877.12	3000	3000	3000
	60	0	0	0	5.6	1061.56	2783.18	3000	3000	3000
	70	0	0	0	0	153.8	2648.6	3000	3000	3000
	80	0	0	0	0	0.02	2455.32	3000	3000	3000
	90	0	0	0	0	0	2181.84	3000	3000	3000
	100	0	0	0	0	0	1771.42	3000	3000	3000

Pop. Rate	Step	Close Circle Weight 0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
40%	0	4000	4000	4000	4000	4000	4000	4000	4000	4000
	10	3816.08	3892.22	3953.96	3990.86	4000	4000	4000	4000	4000
	20	3476.66	3661.72	3836.3	3958.26	3998	4000	4000	4000	4000
	30	2891.82	3243.96	3586.56	3871.52	3992	4000	4000	4000	4000
	40	1922.96	2543.78	3144.5	3687.22	3975	4000	4000	4000	4000
	50	601.28	1446.36	2435.16	3375.68	3941	4000	4000	4000	4000
	60	6.92	212.28	1349.04	2893.76	3889	4000	4000	4000	4000
	70	0	0.14	196.2	2162.98	3818	4000	4000	4000	4000
	80	0	0	0.24	1061.26	3721	4000	4000	4000	4000
	90	0	0	0	122.54	3588	4000	4000	4000	4000
	100	0	0	0	0.34	3412	4000	4000	4000	4000
50%	0	5000	5000	5000	5000	5000	5000	5000	5000	5000
	10	4975.22	4992.36	4998.98	5000	5000	5000	5000	5000	5000
	20	4951.2	4984.6	4998.26	4999.96	5000	5000	5000	5000	5000
	30	4926.56	4977.52	4997.52	4999.94	5000	5000	5000	5000	5000
	40	4902.12	4970.64	4996.42	4999.94	5000	5000	5000	5000	5000
	50	4876.34	4963.54	4995.76	4999.9	5000	5000	5000	5000	5000
	60	4846.78	4956.7	4995.22	4999.88	5000	5000	5000	5000	5000
	70	4818.3	4949	4994.44	4999.86	5000	5000	5000	5000	5000
	80	4785.4	4941.16	4993.8	4999.8	5000	5000	5000	5000	5000
	90	4746.06	4932.94	4993.16	4999.78	5000	5000	5000	5000	5000
	100	4698.52	4922.62	4992.54	4999.78	5000	5000	5000	5000	5000
60%	0	6000	6000	6000	6000	6000	6000	6000	6000	6000
	10	5999.84	6000	6000	6000	6000	6000	6000	6000	6000
	20	6000	6000	6000	6000	6000	6000	6000	6000	6000
	30	6000	6000	6000	6000	6000	6000	6000	6000	6000
	50	6000	6000	6000	6000	6000	6000	6000	6000	6000
	70	6000	6000	6000	6000	6000	6000	6000	6000	6000
70%	0	7000	7000	7000	7000	7000	7000	7000	7000	7000
	10	7000	7000	7000	7000	7000	7000	7000	7000	7000
	50	7000	7000	7000	7000	7000	7000	7000	7000	7000
	100	7000	7000	7000	7000	7000	7000	7000	7000	7000
80%	0	8000	8000	8000	8000	8000	8000	8000	8000	8000
	10	8000	8000	8000	8000	8000	8000	8000	8000	8000
	50	8000	8000	8000	8000	8000	8000	8000	8000	8000
	100	8000	8000	8000	8000	8000	8000	8000	8000	8000
90%	0	9000	9000	9000	9000	9000	9000	9000	9000	9000
	10	9000	9000	9000	9000	9000	9000	9000	9000	9000
	50	9000	9000	9000	9000	9000	9000	9000	9000	9000
	100	9000	9000	9000	9000	9000	9000	9000	9000	9000