Agent-Based Modeling of Society Resistance against Unpopular Norms

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People live in a society adhering to different types of norms, and some of these norms are unpopular. This paper proposes an agent-based model for unpopular norm aversion. The proposed model is simulated asking important "what-if" questions to elaborate on the conditions and reasons behind the emergence, spreading and aversion of unpopular norms. Such conditions can thus be analyzed and mapped onto the behavioral progression of real people and patterns of their interactions to achieve improved societal traits particularly using the new social landscape dominated by digital content and social networking. Hence, it can be argued that careful amalgamation of social media content can not only educate the people but also help them in an aversion of undesirable behaviors such as retention and spreading of unpopular norms. Simulation results revealed that to achieve a dominant norm aversion, an agent population must incorporate a rational model, besides, active participation of agents in averting unpopular norms.

Povzetek: Razvit je agentni sistem obnašanja množic, ki omogoča analizo odpora proti nezaželenim normam.

1 Introduction

Social norms are concepts and practices prevalent in a society [7]. Formally, "Norms are practical prescriptions, permissions, or prohibitions, accepted by members of particular groups, organizations, or societies, and capable of guiding the actions of those individuals" [21].

Norms are accepted which means that their existence is evident from empirical inquiry. However, there is a contradiction in the viewpoint of the notion of existence. One view of norms existence (acceptance) is internalized that incorporates it into individuals' identity [21, 1]. The other view uses the intentions of individuals' as the criterion for norm acceptance instead of the identity of individuals [21]. Therefore, conforming/accepting a norm corresponds to the first view while following a norm relates to the second view [3]. This distinction allows thinking of a norm even without accepting it [21]. Norms describe a collective behavior of groups, organizations, or societies but they are the collective outcome of individuals' cognition.

Norms have the power to transform into actions. This can lead to norm transformation as well. Brennan et al [3] have distinguished between conforming and complying (following) with norms. Similarly, they differentiated between avoiding and acting opposite to norms. These actions are norm guided and in the absence of a norm, an action would not be performed or it would be performed but not in a similar fashion [21].

Norms play an important role in the development of social order [30]. They can change, create and affect behaviors. On the other hand, behaviors are capable of changing, creating and affecting norms [15]. Individual behavior affects the behavior of other individuals in its range of influence [8]. The process is often defined as norm being "externalized". These externalities are able to reproduce a regulatory impact on individuals' behavior [12]. According to Christine Horne, a higher degree of norm enforcement have large sanctioning benefits [9]. She designed a norm enforcement theory with the following features. In the case of group welfare, sanctioning benefits have a positive effect on norm and metanorm enforcement. However, the sanctioning cost has a negative effect on norm enforcement. In the case of social relations, interdependence has a positive effect on norm enforcement. Similarly, sanctioning cost and interdependence have a positive effect on metanorm enforcement. Meta-norms are a particular type of norms that regulate enforcement. Interdependence means the extent to which individuals value their relations. The experimental analysis of the theory of enforcement has revealed that theories that do not consider social relational contact may produce faulty predictions.

Generally, an individual in a society is expected to behave according to societal norms. However, the equation is not that simple. Following a societal norm does not mean that an individual is accepting it. There may be a number of conditions and incentives that force an individual to follow a social norm [21]. This clearly distinguishes the distinction between following and conforming to the norm. If a norm is not confirmed or accepted from the inside of an individual, just following it as a visible trait is of weaker intensity. Hence, in the case of an individual, a norm can be followed as a result of social pressure, but not accepted, if the individual's personal belief does not correspond to it. Contrarily, an individual may accept/conform to a norm, if personal belief corresponds to following it. Christine Horne [10] has emphasized on relationships, which are more important than individual perception about norms. She argues that these relationships can even persuade an individual to enforce a norm, even if there is no apparent benefit of doing it. This situation becomes interesting when a particular norm is unpopular in nature.

Unpopular social norms are those norms with which the majority of people do not agree or believe in it internally. In fact, people personally do not agree with unpopular norms but still stick to them. Individuals' may even unintentionally enforce others to follow them. Such cases in sociology are dealt through a dilemma called, Emperor's Dilemma, as illustrated by Nkomo in [24]. Emperor's dilemma relates to a tale in which everyone shows fake admiration for a new gown worn by an emperor even though the emperor was naked. The cunning gown designers announced that the (non-existent) gown would not be visible to those who are not loyal to the emperor or who are really dumb. The fear of being punished and of being identified as having inferior societal traits, no one spoke the truth. The truth that the emperor was in fact naked.

It is evident that the Emperor's Dilemma is demonstrated in many places around the world in one way or the other. Whether it is foot-binding in neo-Confucian China or intercousin marriages and dowry in Asia (indicated by Blake in [2] and Hughes in [11], respectively), the nature of the thought process is the same. People do not reveal what they really believe from the fear of being identified as ignorant or anti-social.

It is not that harmful if unpopular norms are followed at an individual level. However, when a large population adopts unpopular norms, following it becomes a kind of default behavior that might influence the neutral part of the population. As a consequence, it has been observed that people even start enforcing unpopular norm which they disapprove in private. This behavior is generally termed as false enforcement. Willer et al. in [29] focused on finding out the reasons for false enforcement. According to them, people falsely enforce unpopular norms to create an illusion of sincerity rather than conviction. They performed experiments using two scenarios, namely, wine tasting and text evaluation. Experimental results revealed that people who enforced a norm even against their actual belief, in fact, criticized different alternate variations of an unpopular norm. In short, their outcomes indicate that how social pressure can lead to false enforcement of an unpopular norm.

Un-popular Norms (UNs) could have an adverse impact on society and it is, therefore, sometimes necessary to oppose and possibly avert them. To achieve this goal, it is important to know the conditions which enable the persistence of unpopular norms and models that support possible aversion of these norms. This study attempts to elaborate on the conditions and reasons behind the emergence, spreading and aversion of unpopular norms in a society, using a theory-driven agent-based simulation.

The rest of the paper is structured as follows. Section 1 introduced the research work presented in this work. Related work is provided in section 2. The current models and then the proposed model is presented in section 3. Detailed analysis and comparison are provided in 4. Section 5 ends this paper with conclusions and future direction of this work.

2 Related work

The propagation and transformation of norms co-evolve with each other. Norms propagate through diffused influence. Since the subjects being influenced may have their own perspective, they may decide to adhere or reject it. As a result, the reciprocating influence of the subjects may transform the norm itself. According to Macy and Flache, exploration of scenarios of such a nature has been a subject of complex adaptive systems and they are investigated by developing agent-based models [18]. Understanding the emergence of norms in a society of agents is a challenge and an area of ongoing research [27].

Studying norms in society have been one of the research focus of agent-based modeling community. Theoretical studies on norms such as those conducted by Conte and Castelfranchi [6] and Meneguzzi et al. [20] explored that agent are supposed to comply with social norms. The sense of punishment from the society is evident as the predominant factor behind compliance of norms [4]. Studies conducted by Sanchez-Anguix et al. [25] and Sato and Hashimoto [26] focused on the emergence of norms and they described strategies showing how norms prevail in a society. This is basically governed by societal influence. Agents set their goals and frequently change their behavior based on societal influence until a global equilibrium in achieved [27]. Though lots of work has been done on the emergence and prevalence of norms, very limited is carried out for the aversion of unpopular norms. To the best, our knowledge, our previous work [31, 22, 23] is the only agent-based study on this exciting research area. Willer et al. have pointed out many "empirical cases in which individuals are persuaded to publicly support behaviors or beliefs that they privately question" [29]. The term, Preference falsification, coined by Kuran [17] is defined as "the act of misrepresenting one's genius wants under perceived social pressures". According to him, an equilibrium is the sum of three utilities namely, intrinsic, expressive, and reputation. The intrinsic utility is about an individual's personal satisfaction being part of the society. The expressive utility is about an individual gain in the response of presenting himself/herself to be what is expected. The utility that is acquired through the reaction of others is termed as reputation utility. The concept of an unpopular norm is very close to the concept of preference falsification, in which individuals publicly lie about their privately held preferences [16]. According to Makowsky and Rubin [19], such societies are "prone to cascades of preference revelation if preferences are interconnected - where individuals derive utility from conforming to the actions of others". Further, "ICTs and preference falsification complement each other in the production of revolutionary activity. The former facilitates the transmission of shock while the latter increases the magnitude of change that arises after a shock." The utility acts in two different ways in the propagation of unpopular norms. At one end, it can force an individual to follow an unpopular norm, or even falsely enforce it. On the other end, it can propagate an opposite sentiment as a result of private preference revelation. There is a number of evidence that a minority of activists (capable of revealing their private preferences on will) can make a big difference but in a conducive environment [13]. So, the relevant question in this context becomes *"Can a minority of activists change an unpopular norm adopted by the majority?"*.

3 The proposed extended model

To avert UNs, it is important to understand conditions that might help to stop the propagation of these norms. Particularly, it is imperative to find the conditions necessary to establish an alternative norm - a reciprocal norm of prevailing UN, and the conditions that enforce people other than activists to follow the alternate norm. This section first introduces the social interaction model for following UNs proposed by Centola et al. [5]. It, then, provides briefly our previous extension to this model followed by the proposed extension in this paper.

3.1 Centola's model of norm aversion

Centola's model [5] is capable of elaborating the conditions and reasons behind the emergence, spreading, and aversion of UNs in society but using theory-driven approach. Consider an Un-popular Norm (UN) prevailing in a society. Assume that a minority of the population truly believe in it due to some vested interest. Agents representing this population are termed as True Believerss (TBs). Contrarily, a majority of the population do not believe in the UN. Agents representing this population are termed as Dis-Believerss (DBs). Figure 1(a) illustrates a sample distribution scenario.

Centola's model is based on four variables explained below:

1) Belief: an agent's belief in UN which is 1 in case of TBs and -1 in case of DBs.
2) Compliance: means that an agent is complying with a UN or not? Initially, all TBs are complying ($compliance = 1$) and DBs are not complying ($compliance = -1$).
3) Enforcement: is an agent influence on the neighborhood. Starting with a default value of 0, it can either be -1 or 1.
4) Strength: is an agent's resistance against compliance of a UN.

An agent *i*'s belief is a static value. The value of compliance may change using Equation 1.

$$compliance_i = \begin{cases} -belief_i \;\; if\ (\frac{-belief_i}{N_i} \times NE_i) > strength_i \\ belief_i \qquad\qquad\qquad\qquad otherwise \end{cases} \tag{1}$$

$$enforcement_i = \begin{cases} -belief_i,\ if\ (\frac{-belief_i}{N_i} \times NE_i) > (strength_i + k) \bigwedge (belief_i \neq compliance_i) \\ belief_i,\ if\ (strength_i \times enforcement\_need_i > k) \bigwedge (belief_i = compliance_i) \\ 0,\ \ otherwise \end{cases} \tag{2}$$

Where, NE_i = count of (Moore's) neighbors enforcing opposite belief and N_i = count of (Moore's) neighbors. This means that an agent's decision to comply with UN or not is dependent on the enforcement of opposite belief by the neighborhood. If NE_i is greater than the strength of a DB, the agent would comply against its belief. Since, TBs compliance (which equals their belief about a UN) and strength are already equal to 1, Equation 1 would not change the compliance value of TBs.

When compliance is decided, an enforcement decision is made next. Enforcement value may change using Equation 2.

Equation 3 is used to compute $enforcement\_need_i$ - that is the need of enforcement reflecting influence of neighborhood compliance.

$$enforcement\_need_i = \frac{(1 - \frac{belief_i}{N_i}) \times NC_i}{2} \tag{3}$$

Where, NC_i = number of (Moore's) neighbors whose

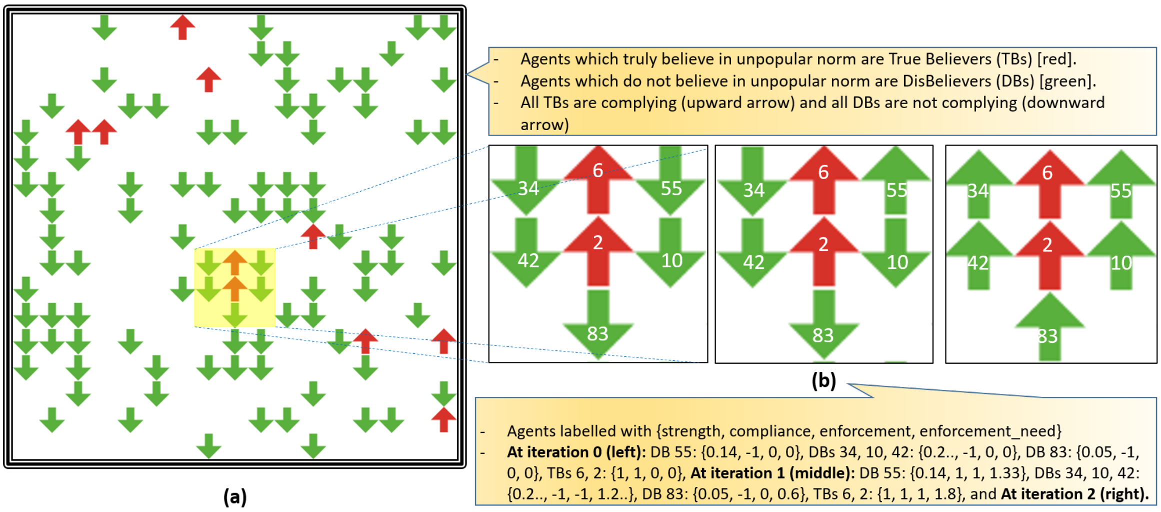

Figure 1: (a) Simulation set-up for 100 agents including 10% TBs. Initial values: TBs (belief = 1, strength = 1.0, compliance = 1, enforcement = 0), DBs (belief = -1, strength = [0.01-0.29], compliance = -1, enforcement = 0). (b) Changes in arrow directions in response of the application of Centola's model.

compliance is different than the agent's belief.

When an agent's belief is equal to compliance (true is the case of TBs and starting values of DBs), then the enforcement will be equal to belief but only when strength $\times$ enforcement_need of an agent is greater than a threshold variable k. Otherwise, it would remain 0. Since, the strength of DBs is kept very low, thus the condition would not result in enforcing -1 value by DBs. This condition will always enforce a value of 1 by TBs. On the other hand, when an agent's belief is not equal to compliance (true is the case of DBs with belief -1 and compliance 1 when Equation 1 is applied), the enforcement will be equal to the negation of belief but only when the enforcement of opposite belief in the neighborhood is greater than strength plus k value of the agent. This means that such a DB itself start enforcing a UN.

For example, the TB with ID 6 (see Figure 1 (b) - middle) uses Equation 3 to calculate the enforcement_need value equal to 1.6 for $belief_i = 1$, $N_i = 5$ and $NC_i = 4$. Thus, the value of compliance for the agent (from Equation 1) remains equal to its belief, because, neighborhood enforcement $(-(1)/5 \times 0$, where $0 = NE_i)$ is not greater than its strength 1. However, the second condition of Equation 2 changes enforcement from 0 equal to 1, because, the strength value of 1 multiplied with enforcement_need value of 1.6 gives a much greater than the enforcement threshold k which is considered 0.2 in this case. The same explanation applies to TB named 2.

DB (BD check it please), numbered 55 (see Figure 1(b)) applies Equation 3 to get the enforcement_need value equal to 1.33 for $belief_i = -1$, $N_i = 3$ and $NC_i = 2$. In this case, the value of compliance for the agent (from Equation 1) changes to the opposite of its belief, because, neighborhood enforcement $(-(-1)/3 \times 2$, where $2 = NE_i)$ is greater than its strength value of 0.14. The first condition of expression 2 changes the enforcement value from 0 equal to 1 as neighborhood enforcement $(-(-1)/3 \times 2$, where $2 = NE_i)$ is much greater than the enforcement threshold k (0.2 in this case) plus strength (0.14).

There are some DBs that do not comply at this point. For example, DB 34 by using Equation 3 calculates the enforcement_need value equal to 1.2 for $belief_i = -1$, $N_i = 5$ and $NC_i = 2$. The value of compliance for the agent (from Equation 1) remains unchanged, because, the neighborhood enforcement $(-(-1)/5 \times 1$, where $1 = NE_i)$ is not greater than its strength value of 0.216. The second condition of Equation 2 would make enforcement from 0 equal to -1, because strength (0.216) multiplied with enforcement_need (1.2) is slightly greater than the enforcement threshold k considered 0.2 in this case. The same applies to DB 10 and 42. Contrarily, the enforcement of DB 83 remains 0. These DBs, however, start complying at next iteration (see Figure 1 (b) - right) due to combined enforcement of their neighbors.

3.2 Our previous extension

Since, acpdb compliance in basic centolla's model is undesirable, in our previous work [31], we extended it and introduced a special kind of DBs (called Activists (ACTs)) with more desire to avert (act against) a UN. These ACTs are triggered by the presence of TBs in the surrounding, particularly who are enforcing. Their strength is progressively incremented proportionally to the intensity of enforcement from TBs. The strength of an ACT is calculated using Equation 4.

$$strength_i = strength_i + (\frac{E_{jb}}{N_i}) \tag{4}$$

Where, E_{jb} = is the number of enforcing TBs.

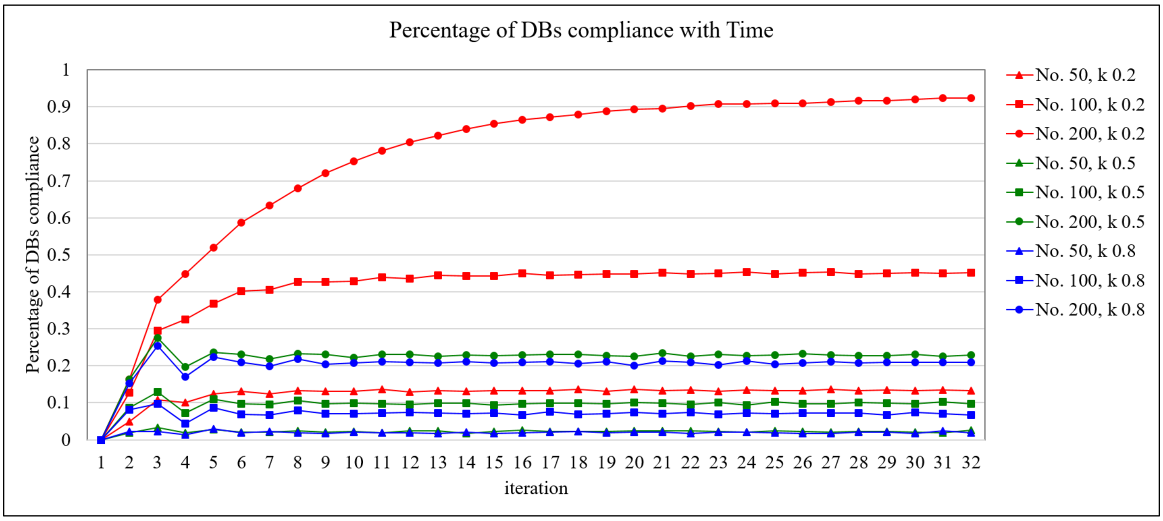

Figure 2: Simulation results of the basic Centolla's model for various scenarios based on number of agents (considered 50, 100, and 200) and threshold value k - showing an agent's desire to comply (considered 0.2, 0.5, and 0.8).

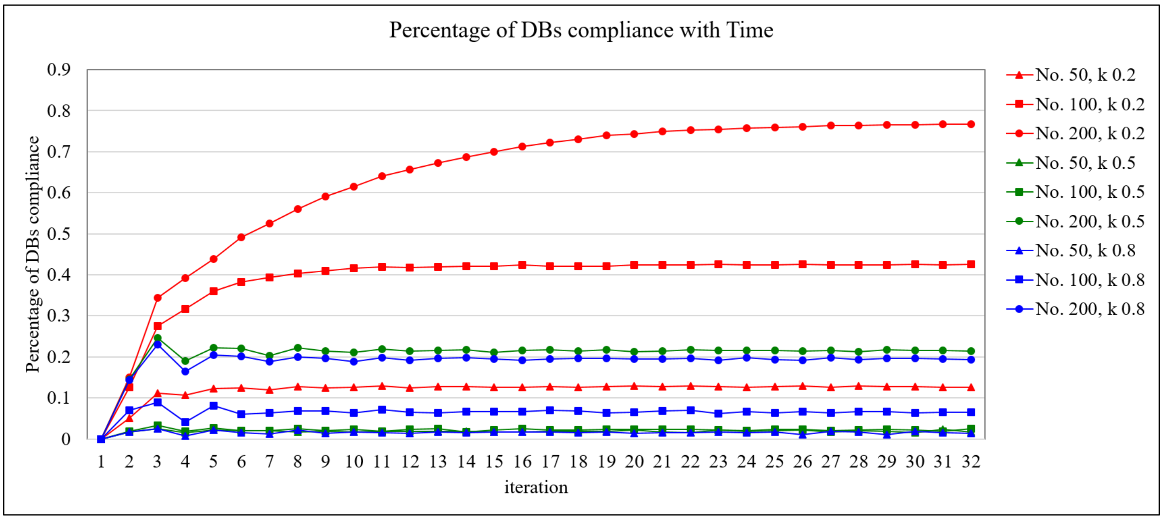

Figure 3: Simulation results of our previous extension to Centolla's model for various scenarios based on number of agents (considered 50, 100, and 200) and threshold value k - showing an agent's desire to comply (considered 0.2, 0.5, and 0.8).

3.3 The proposed extension

In this paper, the model is further extended to incorporate the decision-making of a DB as a result of neighborhood condition. It is proposed that DBs (who are not ACTs) should not be considered as entirely a numb entity. We propose a decision-making model represented in Equation 5. In this model, the strength of DBs (who are not ACTs) is changed (increased or decreased) based on its type being either "optimistic" or "pessimistic". The difference between percentage of enforcing TBs (termed as, P_{jb}) and percentage of complying DBs (termed as, P_{jd}) is divided by neighborhood density (N_i) times the fraction of DBs of that type (consider *opt* for an optimistic and "$1 - opt''$ for a pessimistic DB). If an agent belongs to the optimistic category, its strength would be increased/decreased based on the difference of "true enforcement" (represented as P_{jb}) and "false compliance" (represented as P_{jd}). When fast compliance is more then the strength will decrease. On the other hand, when true enforcement is more then the strength will increase.

4 Evaluation and results

4.1 Simulation environment

NetLogo [28] - a popular agent-based simulation tool with support for grid-based spaces, is used to simulate the work presented in this work. The agents reside on cells of a spatial grid. We have used the concept of Moore's neighborhood to represent the surrounding of an agent - a very

$$strength_i = \begin{cases} strength_i + (P_{jb} - P_{jd})/(N_i \times opt), & if\ i\ is\ optimistic \\ strength_i + (P_{jb} - P_{jd})/(N_i \times (1 - opt)), & otherwise \end{cases} \quad (5)$$

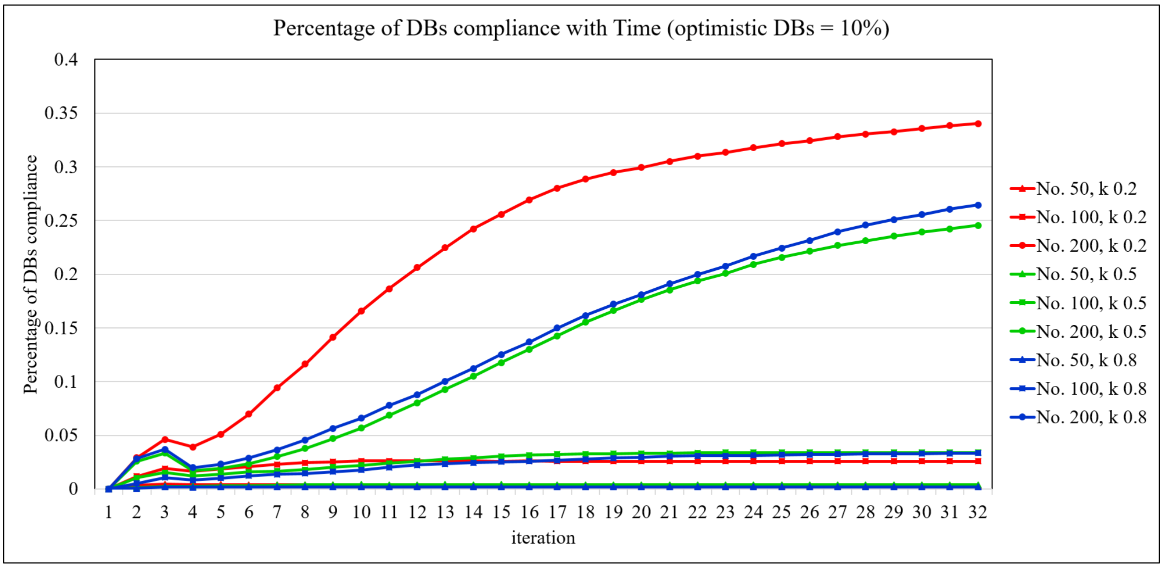

Figure 4: Simulation results of the proposed extension (with 10% agents of total population being optimistic) to Centolla's model for various scenarios based on number of agents (considered 50, 100, and 200) and threshold value k - showing an agent's desire to comply (considered 0.2, 0.5, and 0.8).

popular strategy in many cell-based spatial configurations [14]. For a coarse-grained evaluation, we used a simulation space consisting of a torus of 17×17 cells. Figure. 1(a) provides an illustration of this space filled with 100 agents.

4.2 Results and discussion

4.2.1 Previous findings

Due to the spatial nature of the neighborhood, it was expected that a more dense population is susceptible to more DBs compliance. This fact is evident from the results shown in Figure. 2. Further, DBs's compliance is inversely proportional to the value of k - an agent's desire to comply. Ironically, in all cases depicted in Figure. 2, the population achieves stability always being attracted towards various fixed points.

In our previous work [31], it was observed that in highly dense conditions with a large number of norm aversion ACTs, the aversion of unpopular norms can be achieved. This fact is highlighted in Figure. 3. There is a striking similarity between the basic model and our previously extended model whose results are presented in Figure. 2 and 3 in corresponding order. It is learned that the cases comprise of smaller values of k and a large number of agents are worst than the rest of the cases. A marginal improvement was achieved by introducing the ACTs where comparatively less number of DBs were witnessed complying with a UN.

4.2.2 Current findings: a brief analysis

This model uses optimistic DBs that are intrinsically believing in averting the UN. Simulation work conducted in this paper uses three different numbers of these optimistic DBs, which are counted as 10, 20 and 30% of the total population. It was learned that the proposed model significantly reduces the number of DBs complying with a UN. Even the scenario considered as a worst one (the one comprises of 200 agents and a threshold value k = 0.2) achieved a 100% improvement by drooping compliance rate from 70% to 35%. This is illustrated in Figure. 3 and 4.

When the proposed model is compared with the previous model, it was noted that DBs's compliance comparatively gets worse as the number of agents' increases irrespective of the value of k.

The cases where the number of agents is 200 always perform worse than other cases (comprising of 50 or 100 agents). This can be noticed while comparing the results presented in Figure. 3 with 4). Overall, with an increase in the number of optimistic DBs, the results get improved as witnessed by comparing the results given in Figure. 4, 5, and 6).

4.2.3 Current findings: a detailed analysis and comparison

In this section, we present a detailed analysis of the simulation results. The simulation space for these experiments comprises a torus of 33×33 cells. 1000 agents are placed on cells without overlapping. Figure 7(a) provides this

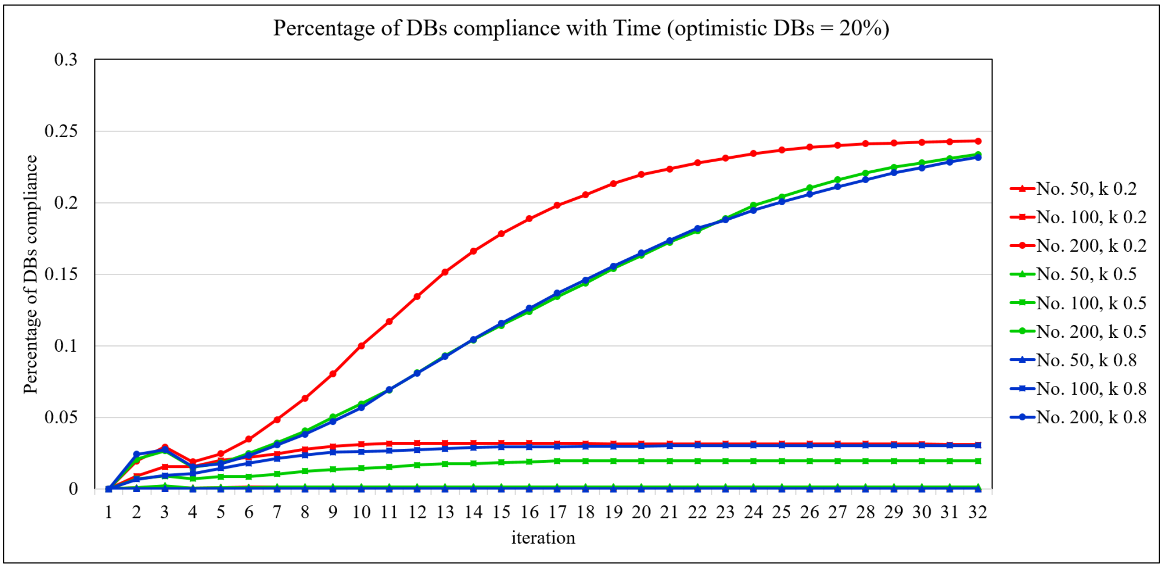

Figure 5: Simulation results of the proposed extension (with 20% agents of total population being optimistic) to Centolla's model for various scenarios based on number of agents (considered 50, 100, and 200) and threshold value k - showing an agent's desire to comply (considered 0.2, 0.5, and 0.8).

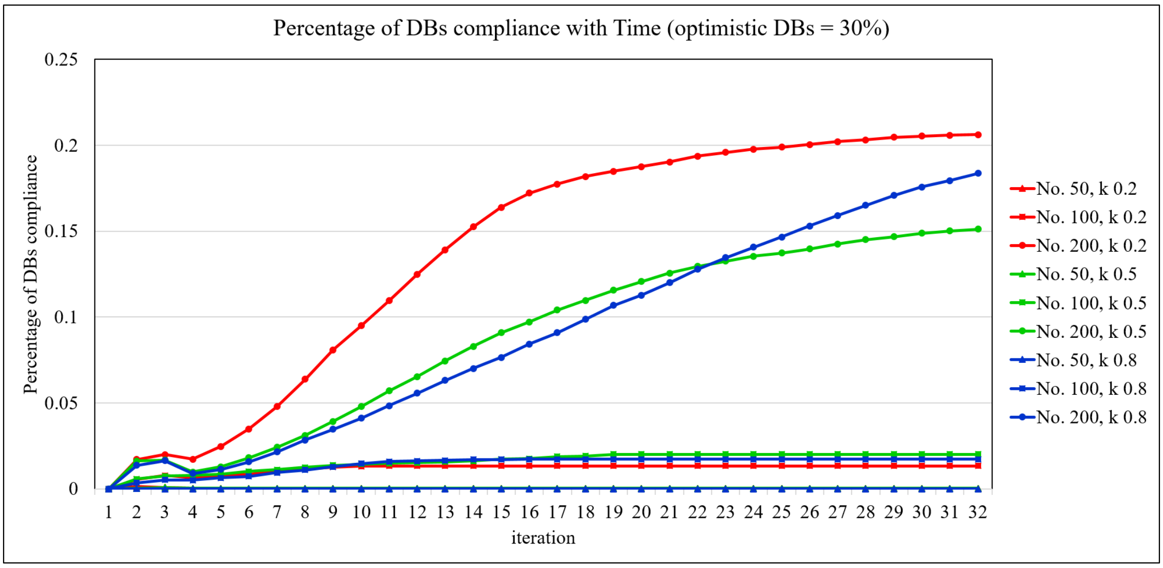

Figure 6: Simulation results of the proposed extension (with 30% agents of total population being optimistic) to Centolla's model for various scenarios based on number of agents (considered 50, 100, and 200) and threshold value k - showing an agent's desire to comply (considered 0.2, 0.5, and 0.8).

setup.

Simulation results are analyzed based on the following four quantities:

1) **DBComplBCount**: is the number of Dis-Believerss which comply with the Un-popular Norm, B, against their belief.

2) **DBFollBCount**: is the number of DBs which do not comply with the UN, B, but follow it against their belief.

3) **DBComplACount**: is the number of DBs which comply with the alternate norm, A, but still do not believe in it.

4) **DBBelACount**: is the number of DBs which comply with the alternate norm, A, and believe in it.

The purpose and intention of the proposed model are to reduce the value of **DBFollBCount** because these agents are unsure and their belief can potentially be averted. The possible aversion may transform agents status from "following" to those which are "complying" with the alternate norm (**DBComplACount**).

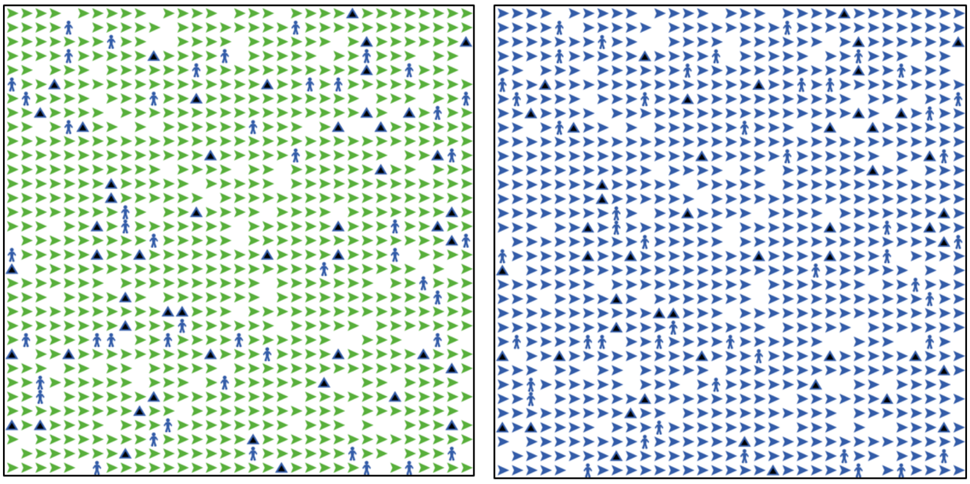

Figure 7: NetLogo Simulation. (a) Setup of 1000 agents with 5% TBs and 5% ACTs. TBs, ACTs, and DBs are represented as blue coloured triangles, blue coloured persons, and green coloured triangles correspondingly. (b) Results of basic Centola model [5]. Equilibrium state, where all DBs now comply with the unpopular norm, B, against their belief.

The basic model proposed by Centola [5] formulates the spread of a UN only. The results of the application of the model settle in an equilibrium state after the 5^{th} iteration. Figure 9(a) visualises the concept presented in Figure 7(b). It is evident from the results presented in Figure 9(a) that all DBs started with following the UN, quickly, started complying with it.

After all, DBs started complying with the norm, B, a change in strategy was tested. The ACTs was activated to play their role as proposed in [31]. The extended model proposed by Zareen et al. [31] reached at an equilibrium between 10^{th} to 12^{th} iteration. Figure 9(b) visualises the concept presented in Figure 8(a).

It is evident from the results shown in Figure 9(b) that DBs started complying with the alternate norm, A, under the influence of ACTs.

The number of DBs which transformed to compliance state merely changed to the following state again. Starting with an increase in the following agents, a decline was observed, however, it did not drop to 0. DBs following and complying to the norm, B, stabilizes with followers more than agents which are complying. As shown in Figure 8(a), DBs in the neighborhood of ACTs started following and complying norm, A, against their belief.

The proposed extended model achieved equilibrium with promising results. Figure 10(a) visualises the scenario presented in Figure 8(b). It is evident from the results given in Figure 10(a) that DBs started complying with alternate norm, A, under the influence of ACTs. Further, the majority of them started complying norm, A, with a belief in it. In response, the number of DBs following the norm, B, reduced to almost nothing.

Finally, we further increased the number of TBs and ACTs to a comparison with the scenarios just discussed. It was learned from Figure 10(a) and 10(b) that the pattern and state changes are similar. However, the aggregate number of DBs in state DBBelACount and DBFollBCount has decreased substantially when compared with the aggregate count of DBComplACount and DBComplBCount. It means that the DBs who believed in the norm, A, was decreased by almost 50% when the number of TBs and ACTs were doubled.

4.2.4 Discussion

The main objective of the proposed model was to reduce the number of disbelievers complying with an unpopular norm, B. It is clear from the simulation results given in Figure 9 that our previous model presented in [31] reduced the number of complying agents to 25% of the whole population as compared with 95% obtained by the standard model. However, 50% agents still follow the norm, B, and only 20% start complying with the alternate norm, A. The credit goes to the introduction of ACTs in the population of agents.

The introduction of optimistic agents in our current extension proposed in this paper significantly improved these results. Though the number of disbelievers complying with an unpopular norm does not change much, however, the majority of disbelievers started believing in alternate norm instead of following an unpopular norm. This is evident from comparing Figure 9(b) and Figure 10(a) with each other.

5 Conclusion

It is argued that for societal good, it is necessary to oppose and possibly avert unpopular norms. This work is an at-

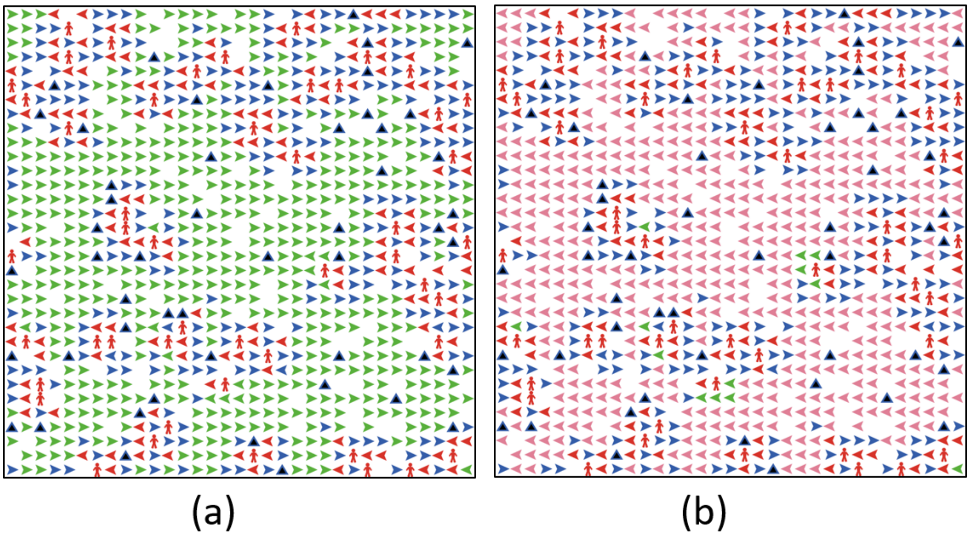

Figure 8: NetLogo Simulation. (a) Setup of 1000 agents with 5% TBs and 5% ACTs. TBs, and ACTs are represented as blue coloured triangles and blue coloured persons correspondingly.The rest of the agents are DBs.Simulation Result of the extended model proposed by Zareen et al. [31]. Equilibrium state, where DBs in the neighborhood of ACTs started following (blue) and complying (red) norm, A, against their belief. (b) Simulation results of the current proposed extended model.

tempt to realise the conditions that result in the emergence of unpopular norms and define situations under which these norms can be changed and averted. It presented an agent-based simulation for unpopular norm aversion. It utilised the reciprocal nature of persistence and aversion of norms to define situations under which these norms can be changed and averted. The simulation results revealed that in addition to agents actively participating in averting the unpopular norm, incorporating a rational decision-making model for normal agents is necessary to achieve a dominant norm aversion. Further, it was learned that the inclusion of true believers and activists play a significant role in norm aversion dynamics.

In short, this study revealed that more educated and socially active individuals are key to reduce undesirable norms in society. The significance of this fact is also applicable to digital societies primarily created by social networking applications nowadays.

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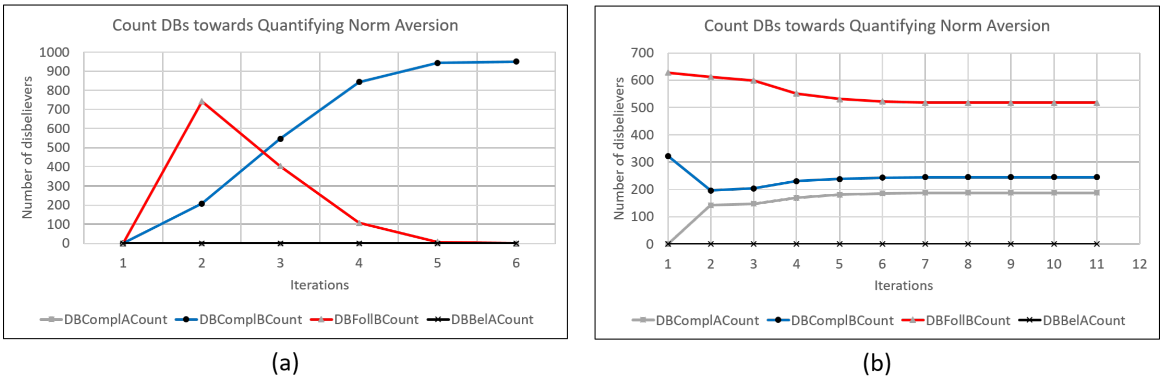

Figure 9: Simulation outcome in terms of number of DBs in various states against time of: (a) the basic Centola's model [5]. (b) the extended model proposed by Zareen et al. [31].

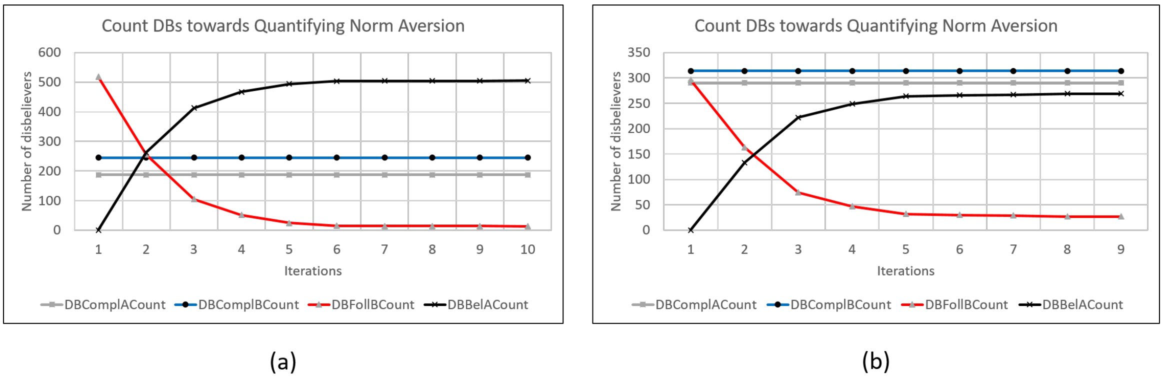

Figure 10: For optimistic agents, the simulation outcome of the proposed extended model in terms of number of DBs in various states against time for the scenarios comprises: (a) 5% TBs and 5% ACTs. (b) 10% TBs and 10% ACTs.

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