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Norm emergence in agent societies formed by dynamically changing networks

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Abstract. In this paper we describe how our previously proposed role model agent mechanism for norm emergence can be applied to artificial agent societies with network topologies that are changing dynamically. Dynamically changing network topologies account for agents joining and leaving the network and the links that are created and removed between agents in a society. In order to construct a dynamically changing network we have adopted a model representing agents as particles colliding in a social space. We demonstrate that the role model agent mechanism for norm emergence works on top of dynamically created network topologies that represent social relationship structures.

Keywords: Norms, software agents, emergence, networks, topology

1. Introduction

Social norms are behaviours that are expected by the members of a society. Software agents that work on behalf of human agents should possess a mental model of norms they are expected to follow. These norms are either specified by a norm enforcer or an authority in a top-down fashion or can emerge in a bottom-up fashion through agent interactions. We are interested in studying how norms might emerge through interactions. The role of network topologies are vital in the study of norm emergence as agent relationships are characterized through social network topologies such as random networks and scale-free networks.

To the best of our knowledge very few multi-agent researchers have considered the role of network topologies for norm emergence. In our previous work Savarimuthu et al. [13] we have described a *role model* agent mechanism for norm emergence and have shown how norms emerge on top of different static network topologies. In the real world, social network topologies are dynamic. People join and leave social groups, so any mechanism for norm emergence should be applicable to dynamically changing network topologies. In this paper we describe the model that we adopted for creating dynamic networks and also the experiments we have conducted on these networks using the role model agent mechanism.

2. Background

2.1. Types of norms

Due to multi-disciplinary interest in norms, several definitions for norms exist. Habermas [8], one of the renowned sociologists, identified norm regulated actions as one of the four action patterns in human behaviour. A norm to him means *fulfilling a generalized expectation of behaviour*, which is a widely accepted definition for social norms. Researchers have divided norms into different categories. Tuomela [17] has categorized norms into the following categories.

- r-norms (rule norms)
- s-norms (social norms)
- m-norms (moral norms)
- p-norms (prudential norms)

The rule norms are imposed by an authority based on an agreement between the members. Social norms apply to large groups such as a whole society (for example, a society of students). The moral norms appeal to one's conscience. The prudential norms are based on rationality. When members of a society violate the societal norms, they are either punished or imposed with certain sanctions.

Many social scientists have studied why norms are adhered. Some of the reasons for norm adherence include:

- fear of authority
- rational appeal of the norms
- feelings such as shame, embarrassment and guilt that arise because of non-adherence.

Elster [5] categorizes norms into consumption norms (e.g. manners of dress), behaviour norms (e.g. norm against cannibalism), norms of reciprocity (e.g. gift-giving norm), norms of cooperation (e.g. voting and tax compliance) etc.

2.2. *Norms and multi-agent systems*

The norms are of interest to researchers in different areas of research such as sociology, economics, psychology and computer science [5] because they help to improve the predictability of the society. Norm adherence enhances co-ordination and co-operation among the members of the society [1,15]. Multi-agent system researchers have borrowed some social concepts such as autonomy and speech act theory to model software agents. Sociologists on the other hand use software agents as a platform to design, test and validate social theories.

Norms in multi-agent systems are treated as constraints on behaviour, goals to be achieved or as obligations [4]. There are two main research branches in normative multi-agent systems. The first branch focuses on normative system architectures, norm representations, norm adherence and the associated punitive or incentive measures [11,2,10,1]. A recent development is the research on emotion based mechanism for norm enforcement by Fix et al. [6].The second branch deals with the emergence of norms.

2.3. *Related work on norm emergence*

Several multi-agent systems researchers have worked on norm emergence [15,9,19,3,18,14]. Boman and Verhagen [3,18] have proposed a norm propagation mechanism based on the concept of *normative advice* (advise from the leader of a society, the Normative Advisor) for spreading norms in an agent society. In our previous work [13] we have extended this model by allowing several distributed role model agents through which the norms can emerge using a bottom-up approach.

Most researchers who have worked on norm emergence [15,19,3,18,14] have experimented with a society where the agents were completely connected to each other or interacted with one another randomly. Not many have considered the role of network topologies on norm emergence.

James Kittock [9] has experimented with the role of structures in convention emergence. He has noted that the choice of the global structure has a profound effect on the evolution of the system. In particular, he conjectured that the diameter of a network is directly related to the rate of convergence. Recently, Pujol [12] has dealt with the emergence of conventions on top of social structures. He has experimented with norm emergence in connected, random, small world and scale-free networks. In our previous work [13] we have also observed that the network properties such as the diameter of the network and the average path length are crucial in the emergence of a norm.

The current norm emergence work on network topologies is limited by the fact that researchers have only worked with statically created network topologies. Our work in this paper is to apply our role model agent mechanism on top of dynamically changing networks.

3. Architecture of the experimental setup for norm emergence

The architecture of our experimental set up for norm emergence consists of two components, the social network topology and the role model agent mechanism. As shown in figure 1, the networks are constructed using the mobile agent model of Gonzalez et al. [7] (described in subsection 3.1).

N_0 represents the snapshot of a network at time 0. The network is then perturbed by changing the links (adding and deleting links). This results in N_1 at time 1. Using this process we create a set of networks. Once the system that creates the networks reaches a stable state called Quasi-Stationary State (QSS) (described in subsection 3.1), say at time t, we start recording the network topologies. As the second step, we then apply the role model agent mechanism for norm emergence (described in subsection 3.2) on each of the network structures starting from $N_{(t+1)}$ and study the emergence of norms.

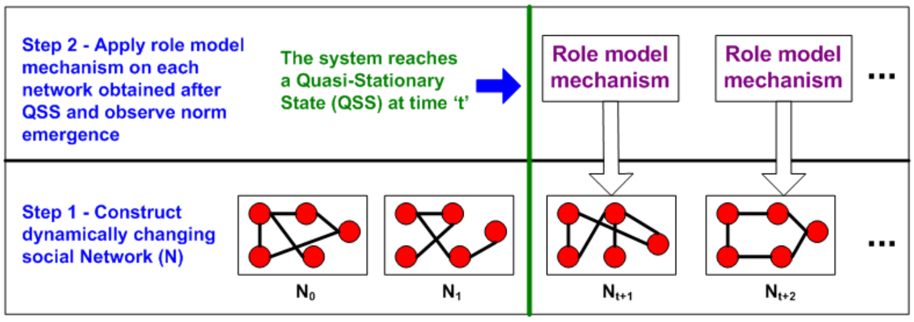

Fig. 1.: Architecture of the experimental setup for norm emergence

3.1. Mobile agent model

Gonzalez et al. [7] have developed a model for constructing dynamically changing networks. In their model they have used the concept of colliding agents (or particles) to construct evolving networks. There are N agents distributed in a two dimensional system (square box) of linear size L which represents an abstract social space. Each agent has the same diameter D. Each agent is initialised with a random starting position. Every agent has the same initial velocity.

When two agents collide, they form a link that represents a social connection between the agents. After each collision both agents move in a random direction. The velocity of each agent is directly proportional to its number of links or contacts (k). The more links an agent has the faster it travels and hence it has an increased ability to attract more links. Each agent has a lifetime which is a random number drawn from a uniform distribution in the interval between 0 and a maximum Time To Live (TTL). Maximum TTL value is also referred to as relationship duration as it represents the maximum time allowed for an agent to create links with the other agents in the society. Once the agent has lived upto a time equal to its maximum TTL, it will be replaced by a new agent with zero links.

Figure 2 shows the snapshot of the visualization of the mobile agent model. The simulation panel on the left shows the mobility of the agents and the collisions. The network panel on the right shows the dynamic construction of the networks.

Each iteration corresponds to one time step. The simulations can be conducted by varying the parameters such as number of balls/particles (N), maximum Time To Live (TTL) and the size of the square box (L). Gonzalez et al. have shown [7] that the system reaches a Quasi-Stationary State (QSS) when the number of simulation steps is greater than twice the TTL ($t > 2*TTL$). At the QSS, the average degree of connectivity $<k>$ of the network (total number of links (M) divided by N) is almost constant (very little fluctuations). Networks that are obtained after the system reaches the QSS are considered stable. Hence, any experimentation on network topologies should only consider those networks that are obtained after QSS is reached.

Our implementation is based on that of Gonzalez et al. [7], but the difference is that they have used continuous time whereas we have used discrete time steps to carry out our simulations.

3.2. The Role model agent mechanism

In our previous work [13] we have developed a mechanism for norm emergence based on role model agents. The role models are agents who the society members may wish to follow. The inspiration is derived from human society where one might want to use successful people as a guide. Any agent in the society can become a role model agent for another agent if that agent asks for advice. The role model agent represents a role model or an advisor who provides normative advice to those who ask for help. In our mechanism, each agent will have at most one leader.

An agent will choose its role model depending upon the performance of its neighbours. The neighbours are the agents that are connected to it based on the underlying network topology. We assume that agents that are connected know each other's performances. This is based on the assumption that people who are successful in the neighbourhood are easily recognizable. We suggest that their success can be attributed to their norms.

Autonomy is an important concept associated with accepting or rejecting request to become a role model. When an agent is created, it has an autonomy value between 0 and 1. Depending upon the autonomy value, an agent can either accept or reject a request from another agent. Once rejected, an agent will contact the

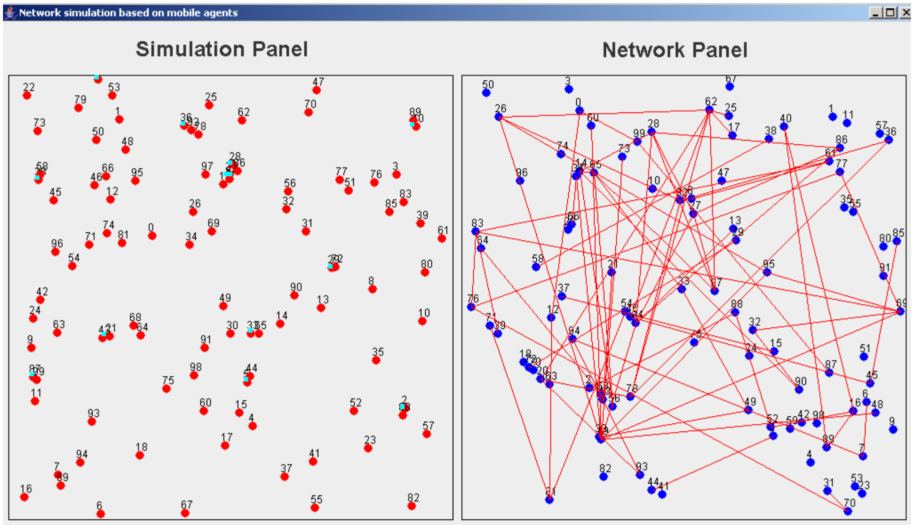

Fig. 2.: A dynamically constructed network with 100 mobile particles

next best performing agent amongst its neighbours. Autonomy of an agent is also related to accepting or rejecting the advice provided by the role model agent. When an agent accepts to follow a role model, it changes its norm such that its norm is closer to the norm of its role model. For example, if agent A's proposal norm is 40 and that of its role model is 50, then A moves closer to its role model by changing its norm to 42. In our mechanism the rate of change of norm of an agent towards its role model is controlled by a parameter.

We have extended the work of Verhagen [18] who has used the concept of normative advice, which a single Normative Advisor for the society provides to all the other agents in the society. In our approach we have used decentralized and distributed normative advisors. The advisors are the role models that other agents can choose to follow.

In this work, we have applied the role model mechanism on top of dynamically changing networks created using the mobile agent model.

4. Norm emergence in a single agent society

In this experiment we demonstrate how norms emerge in a single agent society that is constructed based on dynamically changing networks. The society consists of 100 agents, with their social space simulated by a square box of linear size L=500. The density of the system (N/L^2) is .0004. Once the dynamically changing network reaches the QSS (at a time

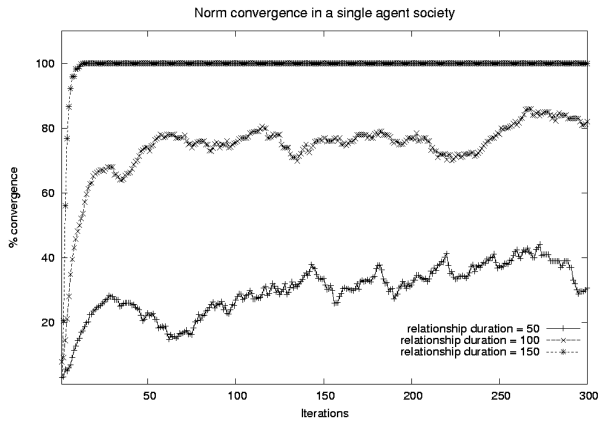

Fig. 3.: Norm emergence on varying the relationship duration

step greater than twice the TTL), we took snapshots of the network structure for the next 300 time steps. These 300 snapshots depict the evolution of dynamically changing networks as shown in step 1 of figure 1.

We then apply the role model agent mechanism that we have designed on top of these 300 networks sequentially. The agents in the network interact with each other in the context of playing the Ultimatum game[1]

[1]The Ultimatum game [16] is an experimental economics game in which two parties interact anonymously with each other. The game is played for a fixed sum of money (say *x* dollars). The first player proposes how to share the money with the second player. Say, the first player proposes *y* dollars to the second player. If the second player

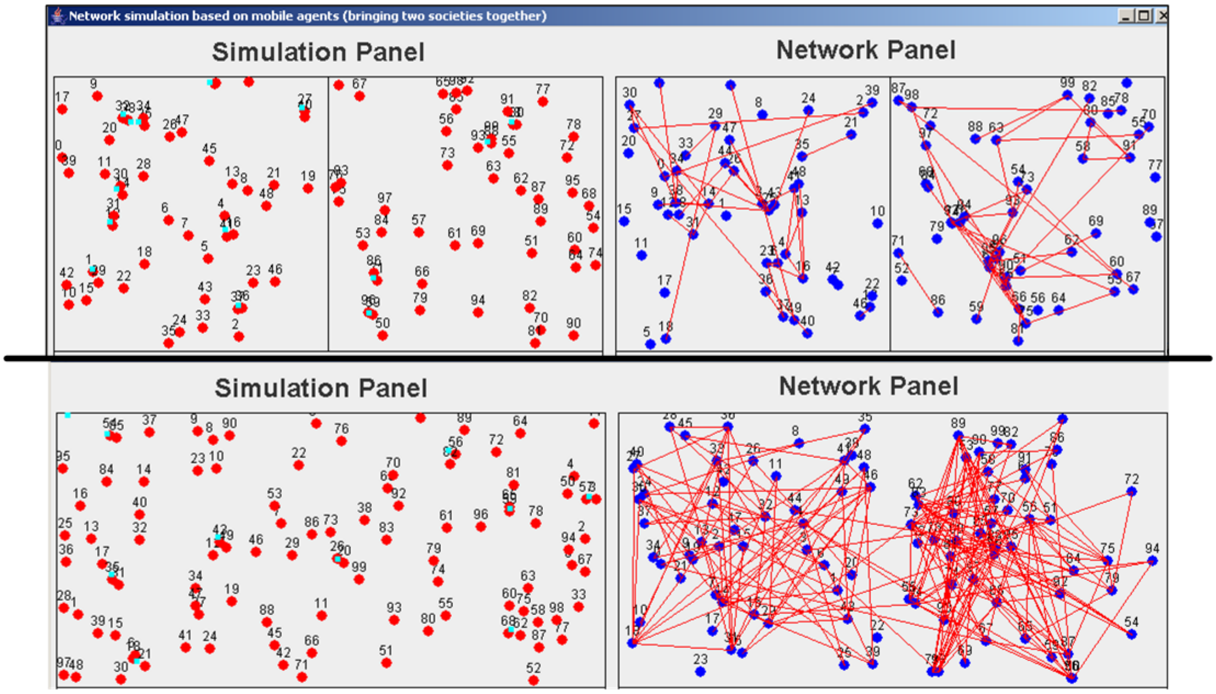

Fig. 4.: A dynamically constructed network with 50 mobile particles in two groups before and after the collapse of the wall between them

[16] for a sum of 100 dollars. We observe how the norms emerge in this scenario.

Each agent has a particular range for acceptance values (say 45 to 55) and proposal values (say 30 to 40). These range of values represent the acceptance and proposal norms. A sample norm for an agent looks like the following where min and max are the minimum and maximum values when the game is played for a sum of 100 dollars.

– Proposal norm (min=30, max=40)
– Acceptance norm (min=45, max=55)

By fixing a particular range for the acceptance norm (say 45 to 55) in the society, we observe how the proposal norm emerges in the society. The agents are initialized with the values for proposal norms based on a uniform distribution.

Figure 3 shows the norm emergence when N=100 for three values of maximum TTL which are 50, 100 and 150. It can be observed that the proposal norm values gradually increase to attain a steady state. It can also be observed that when maximum TTL values are 50 and 100, the norm emergence is not 100% because the underlying network does not have a giant cluster which encompusses all the nodes so that a norm could propagate. In other words, there isn't a path between one node to all other nodes. It has been observed [7] for collision rates approximately equal to 2.04 a giant cluster starts appearing which indicates that there exists a path between any two nodes. When TTL=150, the collision rate exceeds this threshold and hence 100% norm emergence is observed.

Researchers have different notions of the success of norm emergence. For example, Kittock [9] considers a norm to have emerged if the convergence on a norm is 90%. In our case we have 100% convergence as our target for norm emergence. It could very well be 80% too. A norm is considered to exist when it is more prevalent than any of the competing norms. In theory, the convergence value could be any positive number as long as its observed frequency is greater than that of the competing norms.

5. Extending mobile agent model for bringing two societies together

Let us now imagine that two societies with different norms exist. Due to some reason these two societies

rejects this division, neither gets anything. If the second accepts, the first gets *x-y* dollars and the second gets *y* dollars.

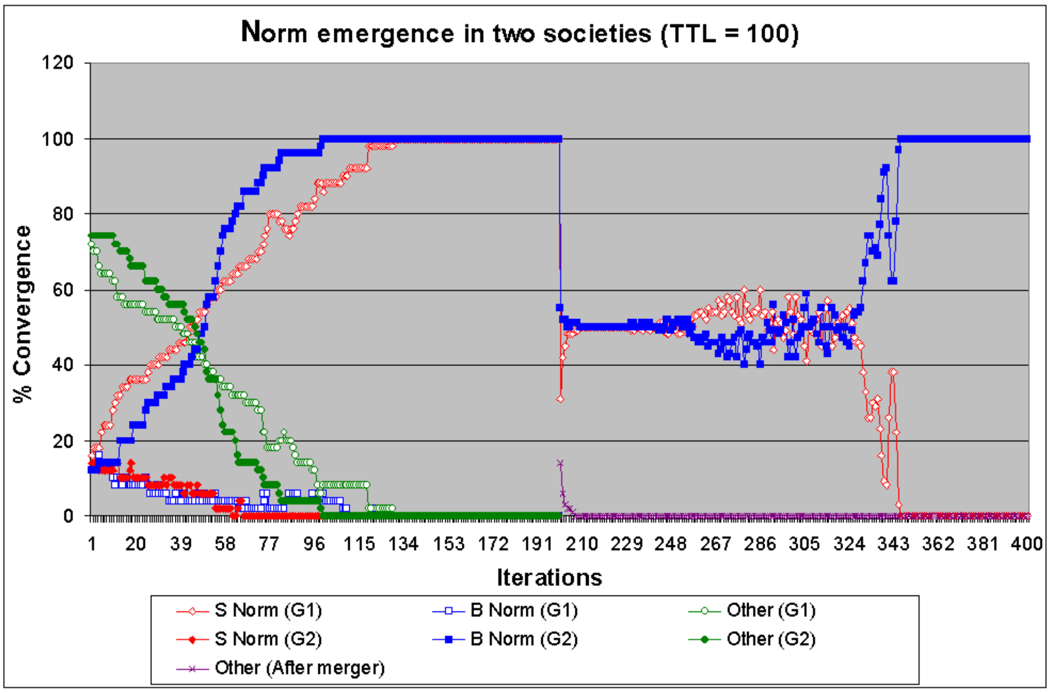

Fig. 5.: Graph showing the convergence results when two societies are brought together (TTL = 100)

come into contact with one another. For example, two societies in the real world can be brought together because of reasons such as earthquakes, famines, floods, war, economic instability etc. In this scenario, it is interesting to study how the norms in these societies emerge.

An important aspect to consider for norm emergence is how we could model the interaction between these two societies and the resultant network topologies. This problem can be addressed by extending the mobile agent model. In the mobile agent model, we can represent the societies by two square boxes and the agents inside each box collide to form a network as shown in the top part of figure 4.

Then, at a particular point in time after the system has reached the QSS, the wall that separates both the societies is removed. When the wall is removed, the agents from one society can interact with the agents in the other society. Initially the mobile agents in the edges of both the boxes collide and over time there is a good dispersion of mobile particles. The bottom part of figure 4 shows a snapshot of two societies coming together based on the mobile agent interaction model.

This approach provides a simple and intuitive model to illustrate how two societies can be brought together. Using this model we can record networks that are created through agent interactions.

6. Norm emergence when two societies are brought together

Suppose there are two societies of agents namely G1 and G2. Each society is expected to evolve a particular proposal norm. The two norms are the selfish norm (S norm) and benevolent norm (B norm). These norms indicate that the agents in the first group will propose less money ($35 to $45 out of $100) to the opponents in an Ultimatum game and the agents in the second group will propose more than a fair share ($55 to $65 out of $100) when playing the Ultimatum game. In our experimental set up, these two norms can be any range of values.

Figure 5 shows the norm emergence patterns in two societies when the maximum TTL of agents is 100. It should be noted that the agents in G1 can have three kinds of norms (which represent three different ranges of values for the proposal norm), the S norm, B norm and also any other norm that is different from the S and B norms. The same holds for G2. Because the initial norm distribution values are assigned using a uniform distribution there will be a small portion of B

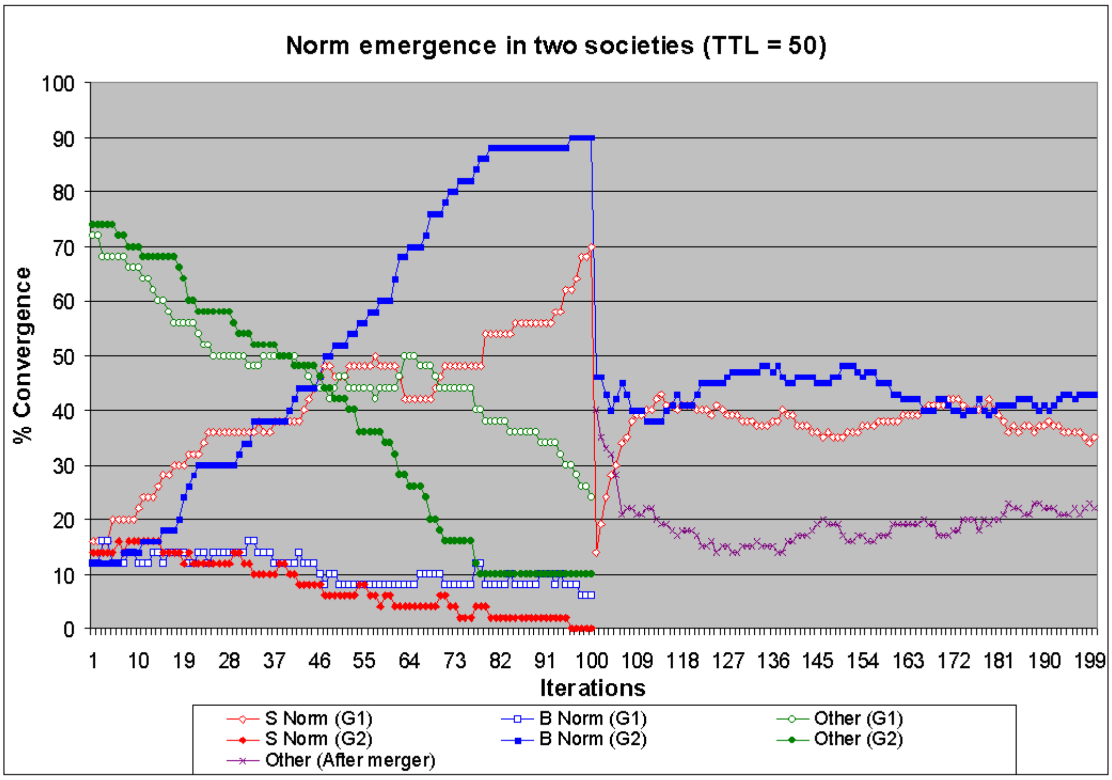

Fig. 6.: Graph showing the convergence results when two societies are brought together (TTL = 50)

norm adherers even in the society that has emerged an S norm. Similarly, there will be a small number of S norm adherers in G2. It should be also noted that we are trying to see if an S norm emerges in G1 and a B norm emerges in G2 and then which of these two norms might emerge after the groups are brought together.

It can be observed from figure 5 that, initially, both groups had a high number of other norm observers (around 70%). As the agents interacted with other agents in the same group, an S norm emerges in G1 and a B norm emerges in G2 before the societies are brought together (before iteration 200). The B norm in G1 and the S norm in G2 and the other norms in both the groups have disappeared before the groups are brought together.

When the wall is brought down, it can be observed that the norm emergence values oscillate closer to 50% and at around 325 iterations the S norm takes over the B norm in the entire society.

This norm emergence on top of a given network is the result of the role model agent mechanism through which each agent in the society chooses a role model. If an agent with S norm chooses an agent with B norm as its role model then that agent will gradually move towards B norm. So, the drivers for emergence are a) the underlying dynamically constructed network and b) the role model agent mechanism that is applied on top of these network structures. We have also observed that, when the same experiment is repeated different norm takes over the society which is based on the underlying dynamically created network.

We also experimented with lower values of maximum TTL. We decreased the maximum TTL from 100 to 50. It can be observed from figure 6 that the two groups have not had a complete norm emergence before the wall is collapsed. The S norm emergence in G1 is around 70% and the B norm emergence of G2 is around 90% before the two groups interact. There are also some agents with other norms. This partial norm emergence is attributed to the lower collison rates as a result of the lower value for maximum TTL. As the life span of the agents are lower, they form a lesser number of links and hence the norm emergence is not 100%. When the agents in both groups are brought together, different types of norms might co-exist. It can be observed that frequencies of both S and B norms are similar and also there are agents with other norms. Again,

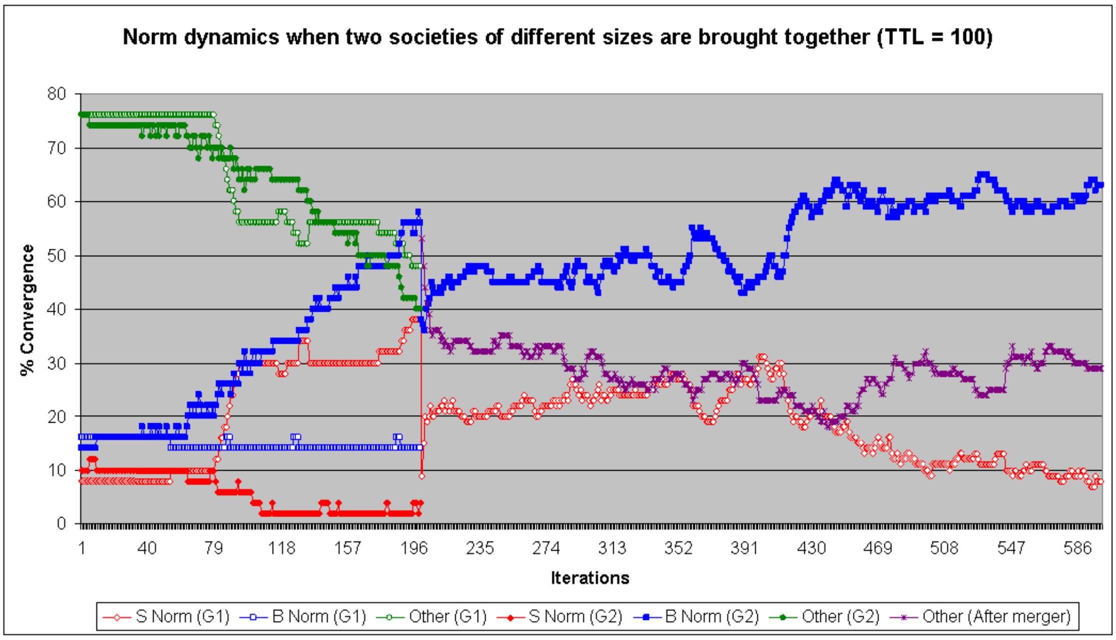

Fig. 7.: Graph showing the convergence results when two societies of different sizes are brought together(TTL = 100)

this behaviour is the result of the lower number of links that are formed between societies due to lower value for maximum TTL.

We also studied the effect of relative population sizes when two societies are brought together. We modified the experimental setup in such a way that there were 25 agents in one group and 75 in another. The density of agents in group 1 was .0004 and the density of agents in group 2 was .000048. This implies that agents in group 1 will interact more frequently than the agents in group 2. The agents in the first group were of the selfish type and they were made to interact more frequently which lead to the creation of a reasonably well-knit society. The agents in the benevolent group were made to interact less frequently to simulate a not so well-knit society. The agents in both the societies had the same maximum TTL which was set to 100. It can be observed from figure 7 that the two groups have not had a complete norm emergence before the wall is collapsed. It should be noted that the S norm is the dominant norm in group 1 and B norm is dominant in group 2 before the collapse of the wall. Overall, B norm seems to be the dominant one in terms of number of adopters. After the collapse of the wall, B norm is more prevalent than the S norm, but still has not been spread to the entire population. The reason for the B norm to maintain is lead is due to the network topology. As the agents of both societies interact, they initially interact at the edges and because the neighbourhood of the agents in society 2 is bigger, the agents from the selfish society are not able to invade and spread the norms. Also, in constrast to the previous two experiments it should be noted that there are quite a few agents with the other norm after the collapse of the wall. This is because there were more number of undecided agents before the collapse of the wall.

When we increased the maximum TTL to 200, the societies converged to the norm of the largest society. This was mainly because the agents with the undecided norms (other norms) adopted one of the norms of society after the wall collapsed and as the larger society had more of these agents the societies converged to the norm of the larger society. When the maximum TTL was decreased to 50, the societies did not converge to any norm as most agents had random norms (other norms) which is attributed to lower collision rates which resulted in smaller number of links between agents.

7. Discussion and future work

In this work we have demostrated that the role model agent mechanism for norm emergence works on top of dynamically evolving networks. Another contribution of our work is to use the mobile agent model to create dynamic networks that depict how two societies can be brought together. Our experimental set-up can be used as a tool to study norm emergence by varying several parameters such as the number of agents (N) and density of agents (ρ), time to live (TTL), initial distribution of norms (uniform, normal etc.), collision rates etc.

The network topologies generated by bringing two societies together can be used not only to test how norms emerge but also in opinion dynamics and influence networks, disease spreading etc. Our experimental set-up can be extended to include bringing more than two societies together and study how norms might emerge in those scenarios. Also, different mechanisms of norm propagation can be experimented with and validated using our approach.

We are also interested in studying the norm dynamics when societies of different sizes are brought together with different levels of norm conformity. In this context we would like to study in detail those conditions under which a smaller tight knit society might sustain and spread its norms to a larger society.

In the future we would like to test the role model agent mechanism on dynamically created networks that are scale-free. This is important because real world networks such as the Internet and social networks are often scale-free. We are planning to provide better representation for norms such as using regular expressions to represent norms instead of simple data types such as integers and booleans. We intend to experiment with the role model mechanism for norm emergence on richer application domains such as electronic commerce (supply chain or auctions).

8. Conclusion

We have previously proposed a mechanism that describes how norms might emerge in agent societies called the role model agent mechanism. We have demostrated that the mechanism works on top of dynamically created networks. In order to create dynamic network structures we have used a mobile agent model based on collisions in a simulated social space. Using the mobile agent model, we created network structures for a single agent society. We have also used this model to demonstrate how two societies can be brought together. We have explained our experimental findings and also discussed our future work.

9. Acknowledgements

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