Social Instruments for Robust Convention Emergence

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Abstract

We present the notion of Social Instruments as mechanisms that facilitate the emergence of conventions from repeated interactions between members of a society. Specifically, we focus on two social instruments: rewiring and observation. Our main goal is to provide agents with tools that allow them to leverage their social network of interactions when effectively addressing coordination and learning problems, paying special attention to dissolving metastable subconventions. Initial experiments throw some light on how Self-Reinforcing Substructures (SRS) in the network prevent full convergence, resulting in reduced convergence rates. The use of an effective composed social instrument (observation + rewiring) allow agents to eliminate the subconventions that otherwise remained meta-stable.

1 Introduction

The social topology that restricts agent interactions plays a crucial role on any emergent phenomena resulting from those interactions [Kittock, 1993; Delgado, 2002; Urbano *et al.*, 2009]. In the literature on emergent behavior in MAS, one active topic is *convention or norm emergence* as a mechanism for sustaining social order, increasing the predictability of behavior in the society and specify the details of those unwritten laws. As conventions help agents to choose a solution from a search space where potentially all solutions are equally good (as long as all agents use the same), the selection of a coordination protocol, communication language, or the selection of the task to be executed in a multitask scenario are pertinent applications of conventions in MAS.

In *social learning* [Mukherjee *et al.*, 2008; Sen and Airiau, 2007] of norms, where each agent is learning concurrently over repeated interactions with randomly selected neighbors in the social network, a key factor influencing success of an individual is how it learns from the "appropriate" agents in their social network.

A number of researchers from several communities (multiagent systems, physics, or economy) have studied the properties of underlying topologies in the convention emergence process [Kittock, 1993; Shoham and Tennenholtz, 1997; Urbano *et al.*, 2009; Delgado, 2002; Delgado *et al.*, 2003]. Most of these research consider a convention as emerged when 90% of the population has converged to the same convention. However, 90% convergence cannot, by definition, be considered a convention, as a convention needs to be shared by the complete population. Initial experiments have shown us how the 90% convergence cannot be improved in specific configurations, i.e. scale free networks.

Along this work we will analyse how agents can develop meta-stable subconventions depending on their position in the of interaction topology. As identified by several authors [Epstein, 2000; Toivonen *et al.*, 2009; Villatoro *et al.*, 2009], meta-stable subconventions interfere with the speed of the emergence of more general conventions. The problem of subconventions is a critical bottleneck that can derail emergence of conventions in agent societies and mechanisms need to be developed that can alleviate this problem. Subconventions are conventions adopted by a subset of agents in a society who have converged to a different convention than the majority of the population. Subconventions are facilitated by the topological configuration of the environment (isolated areas of the graph which promote endogamy) or by the agent reward function (concordance with previous history, promoting cultural maintenance). Even though in some scenarios and applications it could be possible, we assume the general case where agents cannot modify their own reward functions, and therefore the problem of subconventions has to be solved through the topological reconfiguration of the environment.

As agents can exercise certain control over their social network, they can improve one's own utility or social status by modifying it. We define *Social Instruments* to be a set of tools available to agents to be used within a society to influence, directly or indirectly, the behavior of its members by exploiting the structure of the social network. Social instruments are used independently (an agent does not need any other agent to use a social instrument) and have an aggregated global effect (the more agents use the social instrument, the stronger the effect). Specifically we focus on two social instruments:*rewiring* and *observation*. *Rewiring* allows agents to control the links that relate them with other agents by replacing them intelligently. This direct control of the topology of the social network allows agents to control whom they interact with, resulting in increased reward without actually altering the reward function. On the other hand, *observa-*

tion allows agents to obtain partial information of the convention emergence process by observing other agents in the neighborhood. The access to this information allows agents to consider extra information over what they receive from direct interactions. This observation process also has an impact on the reward of the agents by speeding up their convention emergence within the society.

The main contribution of this work is the usage of Social Instruments as mechanisms that speed-up and ensure full-convergence (100% of the population using the same convention). Additionally, in the last part of the paper we argue how a combined social instrument allows the dissolution of subconventions in Scale-Free networks.

2 Proposed Social Instruments

2.1 Rewiring: Intelligent Link Removal and Creation

The Rewiring social instrument allows an agent to remove non-beneficial links with other agents, replacing them with new ones. Agents decide to rewire a link after the number of unsuccessful interactions[1] with another agent crosses a certain *Tolerance* threshold. Agents also need to decide whom they want to establish the new link with. We have developed three different methods:
(1) Random Rewiring: Agents rewire to a randomly selected agent from the population.
(2) Neighbour's Advice: Agents rewire to an agent recommended by a neighbour.
(3) Global Advice: Agents rewire to an agent that is randomly selected by the system from those that have the same strategy.

There are some similarities of our work with that of Griffith's [Griffiths and Luck, 2010]. However, there exist a crucial difference with our approach: they use an evolutionary approach, observing the results of their techniques after the reproduction of a number of generations, and with a certain mutation rate. On the other hand, we use an *online approach* where agents can modify their social network at runtime, without evolving new generations. In addition, our rewiring methods do not access any agent's private information (used only in the Global Advice which is used as a control case), such as their actual reward values.

2.2 Observation

In a social learning scenario, allowing agents to observe the strategy of other agents outside their circle of interaction can provide useful information to support the convention emergence process. However, there has to be a trade-off between observing and interacting. In order to analyze the effects of observation we will allow agents to observe, at certain timesteps, a subset of other agents' states in the population. Therefore, agents will be assigned an *Observation Probability*. Moreover, agents need to know the amount of agents they can observe (*Observation Limit*) and how they want to observe (*Observation Method*). We propose three different observation methods:
(1) Random Observation: Agents observe random agents from the society.
(2) Local Observation: Agents observe their immediate neighbours in the social network.
(3) Random Focal Observation: Agents select one random agent from the society and observe that agent and its direct neighbors.

After the observation process, the agent will choose the majority action taken by the selected observed agents and will reinforce it.

Despite the similarity, this instrument and *mimicking* ([Hales and Arteconi, 2006]) behave differently. With observation, agents only access information that has been previously made public by the observed agent (agent's last played strategy), while with *mimicking*, they access information that can be considered private (list of neighbours and decision strategy function).

3 Model

The social learning situation for norm emergence that we are interested in is that of learning to reach a social convention. We borrow the definition of a social convention from [Shoham and Tennenholtz, 1997]: *A social law (a restriction on the set of actions available to agents) that restricts agents' behavior to one particular action is called a social convention*. For this reason, in our social learning scenario norms are implicit. Agents do not have any internal representation of norms, only preference for one action (the one specified by the norm) over the others.

For the sake of generalization, our framework is built with the most accepted convention emergence model (used by [Delgado *et al.*, 2003; Kittock, 1993; Mukherjee *et al.*, 2008; Sen and Airiau, 2007; Shoham and Tennenholtz, 1997; Walker and Wooldridge, 1995]): agents converge to a convention through repeated bilateral interactions with other agents from their social neighborhood. Any interaction between two agents is represented as an 2-person m-action game. At each time step, each agent is paired with another agent and independently decide their actions. This decision is made without observing the other agent's identity or strategy. In our approach a social convention will be reached once *all* agents are in the same state or consistently choose the same action (the actual state reached or action chosen is immaterial).

As in several other research in convention emergence ([Delgado *et al.*, 2003; Kittock, 1993]), the interactions between agents in our framework are constrained by one of two different underlying structures: (i) a *one-dimensional lattice* with connections between all neighbouring vertex pairs (regular network); and (ii) a *scale-free network*, whose node degree distribution asymptotically follows a power law (irregular network).

As in [Kittock, 1993; Shoham and Tennenholtz, 1997; Villatoro *et al.*, 2009], agents are endowed a limited memory of past interactions (same size for all agents). Agents save in their memory *when* an interaction occurred, the *action* chosen, and the *reward* obtained. As we will see shortly, this information is used differently depending on the type of

[1] Unsuccessful interaction in our convention emergence scenario corresponds to being uncoordinated or not sharing the same convention for that interaction.

strategy decision procedure adopted.

Agents cannot observe the memory, current decision, or reward obtained by the other agent, and hence cannot calculate the payoff for an action before interacting with the opponent.

Once the model of interaction is fixed, we test our social instruments using three well-known strategy selection rules: *(1) Best Response Rule (BRR)* [Mukherjee *et al.*, 2008; Sen and Airiau, 2007], *(2) Highest Cumulative Reward Rule (HCRR)* [Shoham and Tennenholtz, 1997; Kittock, 1993], and, *(3) Memory Based Rule (MBR)* [Villatoro *et al.*, 2009].

The HCRR also specifies the action that each agent has to take in each interaction. On the other hand, for BRR and MBR, agents use the Q-Learning algorithm to estimate the worth of each action, with an exploration rate of 25%.

4 Experiments

In order to reduce the search-space, some simulation parameters have been fixed: a population of 100 agents, with memory of size 5 (for HCRR and MBR), are located in a social network with different topologies: a low clustered[2] one dimensional lattice (lattice with Neighborhood Size = 10), a high clustered one dimensional lattice (lattice with Neighborhood Size = 30), and a scale free network.

Agents are initialized with no preference between the actions available and randomly choose actions with equal probabilities. Presented results are averaged over 25 simulation runs.

4.1 Effects of Rewiring

We have explored the search space of the Tolerance Levels for the three rewiring methods, observing how it affects the convergence time and the number of links rewired when convergence is reached with the different strategy selection rules.

Influence of Rewiring Methods

In general, the *Global Advice (GA)* rewiring method produces the best convergence time due to its centralized nature and access to global information. Nonetheless the decentralized methods, specially the *Neighbour's Advice (NA)* method, also show good performances. The *NA* method improves the *Random Rewiring (RR)* method as it more expediently resolves the subconventions that appear in the one-dimensional lattices during the convention emergence process.

When using the *Neighbour's Advice* method, these subconventions are resolved more expediently. Agents in the frontier use the rewiring instrument as they cross the tolerance level faster than those not in the frontier. For this reason, the *RR* method relinks an agent with a more suitable agent with a probability of $\frac{1}{NumberOfActions}$. In contrast, the *NA* method relinks the agent with another one with the same preference if it is accessible. In case there is no other agent with the same preference to connect with, random rewiring will be applied, obtaining in the worst case scenario, the same results. These results are applicable for the scale-free networks.

[2]Clustering Coefficient is a measure of degree to which nodes in a graph tend to cluster together.

Influence of topology

When observing the effects of the topology, we find that the convergence time is increased under the effects of rewiring when the neighborhood size is increased.

On regular networks, the diameter of the network directly affects the convergence times and the number of components. This effect is due to the clustering coefficient of the network. Lattices with higher neighborhood sizes are less fragmented than those with more restricted neighborhoods. Therefore, when increasing the neighborhood size, the number of links between agents also increases, thereby increasing the clustering coefficient. Highly clustered societies are more resistant to rewiring, as the node that wants to use the rewiring would have to apply it to a higher number of nodes, and then, be rewired to the same number of nodes with the appropriate strategy.

Experimental results also show interesting properties with Scale Free networks: when using the NA rewiring method the number of components is significantly increased. As explained previously, rewiring is applied when two agents surpass their tolerance of unsuccessful interactions and NA will relink to a similar neighboring node. Because of the clustering coefficient of the Scale-Free networks[3], NA will produce the disconnection of subgraphs from the main graph.

We can conclude that rewiring performs better in low clustered societies, producing a stratified population which results in significant reduction in convergence time. In more clustered networks, the tolerance level has to be chosen carefully (depending on the experiment) to produce an effective technique for norm emergence.

4.2 Effects of Observation

In this section we analyze the effects of *observation* as a social instrument when used by agents. We test and compare the three different methods proposed, exploring the search space with a representative range of *Observation Probability* values. To observe the effects of the different observation methods, we fix the *Observation Limit* to 10 for the experiments.

Influence of Observance Methods

Comparing the results from the three Observation methods we observe that the Random (*RO*) and the Random Focal Observation (*RFO*) methods are the most effective ones, and have very similar results, when compared with the Local Observation (*LO*) method. The reason for this phenomenon is to be found on the frontier effect. When agents use the *LO* method, they observe their direct neighbours. If the observing agent is in the frontier area, then, this observation is pointless. However, observing different areas gives a better understanding of the state of the world, and hence the *RO* and the *RFO* methods perform better.

Influence of topology

For the BRR and MBR strategy selection rules, we have observed that the different Observation methods produce a more

[3]The clustering coefficient distribution decreases as the node degree increases.

pronounced effect in societies with higher diameters. We notice that a small percentage of Observation drastically reduces convergence times. The reason for this effect can again be found in the frontier and the subconvention effect previously discussed. Subconventions emerge more readily when the social network has a small diameter and the frontier region represents the unsettled area. These subconventions are more easily resolved at these frontiers by observation rather than by learning through interactions.

5 Combining Instruments: Solving the Frontier Effect.

Our initial results together with the observations narrated by other authors [Epstein, 2000; Toivonen *et al.*, 2009; Villatoro *et al.*, 2009], convinced us that subconventions are problematic obstacles to the emergence of global conventions. These subconventions thrive because of the topological structure of the network where they emerge. To achieve the dissolution of subconventions, they need to be resolved in what we identified as the "frontier" region.

Theoretically, a subconvention in a regular network is not meta-stable, but unfortunately, slows down the process of emergence. On the other hand, in other network types, such as random or scale-free, subconventions seem to reach meta-stable states[4]. Consequently, we have defined *weak frontiers* as the ones that are not meta-stable in regular networks, and *strong frontiers* as the ones generated in irregular networks.

By combining the social instruments presented in Section 2, we have designed a composed instrument for resolving subconventions in the frontier in an effective and robust manner. This composed instrument allows agents to "observe" when they are in a frontier, and then, apply rewiring, with the intention of breaking subconventions. To effectively use this combined approach, agents must first recognize when they are located on a frontier. We have previously defined a frontier as consisting of the group of nodes in the subconvention that are neighbours to other nodes with a different convention and that are not in the frontier with any other group. The most important characteristic that defines a frontier is the existence of a confrontation. Confrontation occurs when two agents in an interaction do not share the same convention[5].

Before proceeding further, we will define three characteristics of agents with respect to their convention and topological position in the network. An agent is *in equilibrium* if it has the same number of neighbours in its own convention as in the other convention. An agent is a *weak* node if the number of neighbours in its own convention is lower than those in the other, and an agent is a *strong* node otherwise (if the number of neighbours in its own convention is greater than those in the other).

[4]By experimentation, we have observed that around 99% of the generated scale-free networks do not converge (to full convergence) before one million timesteps with any of the decision making functions used in this work.

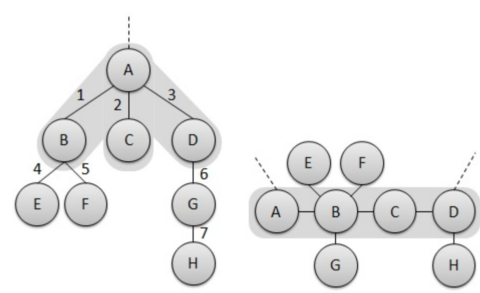
[5]Not sharing the same convention, choosing a different action, or choosing a different state to be, are considered equivalent expressions for our purpose.

In regular networks, two confronted agents are in a frontier region iff: (1) At least one of the confronted agents is in an equilibrium position, and (2) all the neighbours of an in-equilibrium confronted agent are strong nodes.

In irregular networks (such as scale-free topologies) we have performed a more detailed analysis. By taking a snapshot at the end of the simulation of the emergence of such networks, we can extract the regions of the network that remain meta-stable with a convention different than the general convention. After compiling and studying those structures, we identified an abstract substructure that we have defined as *Self Reinforcing Substructures (SRS)*. These substructures, given the appropriate configuration of agents' preferences, do maintain subconventions. These abstract structures are of two types, the *Claw* and the *Caterpillar* (see examples in Fig. 1), and can be found as subnetworks of scale-free and random networks.

The *Claw* SRS is formed by connecting a node with a number of *hangers*[6] connected to it smaller than the number of links with the rest of the network. In the situation where the hangers coordinate to the same convention among themselves and with the connecting node, we have a self-reinforcing structure. For example, in Fig. 1(a), A is the central node, having one connection with the rest of the network and 3 hangers: B (that it is another claw), C (plain hanger) and D (chain's connecting node).

The *Caterpillar* SRS is a structure formed by a central path and from its members can hang other SRSs (such as claws, chains, or plain hangers). For example, in Fig. 1(b), A, B, C, and D are members of the central path, and the other nodes reinforce them.



(a) Claw (b) Caterpillar

Figure 1: Self-Reinforcing Structures

As we have observed, the existence of these SRSS (74% of the generated networks with the methods described in [Delgado *et al.*, 2003] contain SRS) are the main reason why convergence to a 90% level (as observed by [Delgado *et al.*, 2003]) is achieved relatively quickly, but overcoming the last 10% (containing the SRS) is much harder to achieve. Inspired by a previous paper [Sen and Airiau, 2007], we have performed a test varying the amount of players with a fixed

[6]A *hanger* is formed by nodes that are connected to a member of a cyclic component, but which do not themselves lie on a cycle [Scott, 2000], and a *chain* is a walk in which all vertices and edges are distinct.

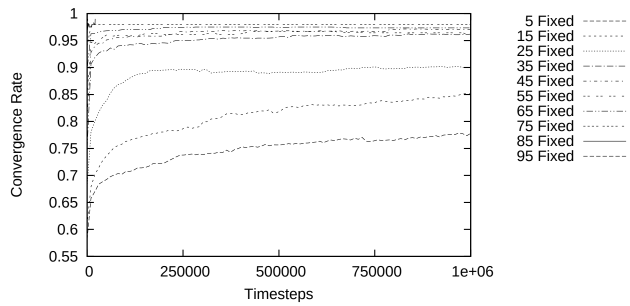


Figure 2: Evolution of Conventions in Scale-Free Networks with Fixed Players.

strategy to observe the dynamics of the emergence of conventions. As shown in Fig. 2, the emergence of conventions in scale-free networks follow the same behavioural pattern amongst them with different amount of fixed players, following a power-law distribution (as the node-degree distribution). The emergence is achieved relatively fast for the majority of the network, however, it is observed an important delay in the rest, where SRSs are located.

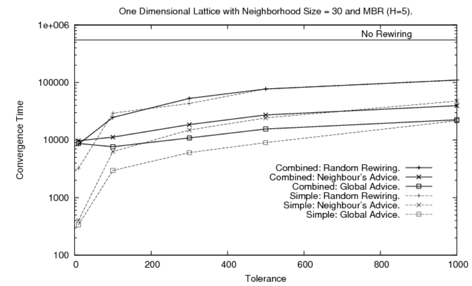
By giving agents the instruments to dissolve these SRS[7], we hypothesize that convention emergence will be achieved faster and full convergence rates will be obtained.

5.1 Results with Combined Instruments

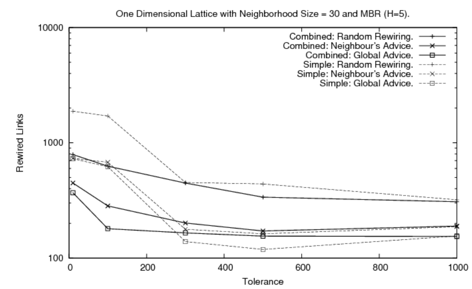
We have conducted exhaustive experimentation with the combined instrument on the three topologies and using the different decision making functions described in the previous section. The use of the composed instrument on the regular networks does not produce an improvement on convergence time with respect to simple rewiring (one example of topology and strategy decision technique can be observed in Fig. 3(a)). However, an important improvement is observed in the number of rewired links (one example of this improvement can be seen in Fig. 3(b)). In general, this improvement is observed for lower tolerances. The reason of this effect is because for higher tolerances rewiring works in the same way as the composed social instrument, but without observing. For those smaller values, the effect is intense, reducing the number of rewiring links down to half of the original value.

On the other hand we observe an important improvement for convergence times when using the composed instrument (with the recognition of SRS) on irregular networks. The results presented in Figure 4 represent the average results from 25 different scale-free networks with and without using the Combined Social instrument. By comparing Figure 4(a) and Figure 4(b) we notice the tradeoff between the improvement in convergence time and the amount of rewiring to be done. The reason of this phenomena is because the Composed social instrument decomposes the SRS differently than the simple rewiring which only rewires the node in the actual frontier.

[7]An agent will use observation to realize it is part of a SRS, and rewiring to dissolve it.

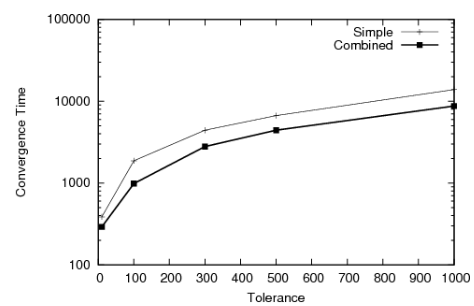


(a) Convergence Time

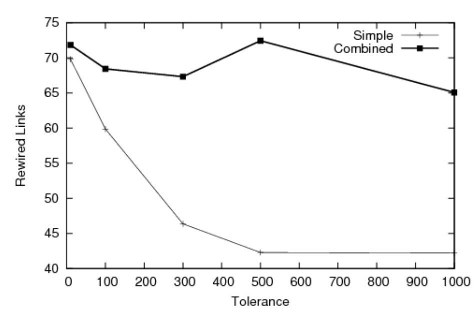


(b) Rewired Links

Figure 3: Comparison with Simple and Combined Social Instruments on Regular Network using MBR.



(a) Convergence Time



(b) Rewired Links

Figure 4: Comparison with Simple and Combined Social Instruments on Scale Free Network using BRR.

6 Conclusions and Future Work

We have introduced the use of *Social Instruments* as tools that facilitate norm evolution. We have identified the characteristics and opportunities for effectively utilizing these social instruments for facilitating norm emergence through social learning. Social instruments are attractive since they do not require centralized monitoring or enforcement mechanisms, normally are extremely easy to use, have very low computational costs, and are scalable to large systems.

Experimental results with the identified social instruments have shown that the emergence of transitory subconventions are the cause of the delay of the emergence of global conventions. From results presented in this paper for the two simple social instruments studied, we observe that the most effective social instruments are those that more expediently solve this subconvention formation problem in the frontier regions.

To the best of our knowledge, this is the first attempt to achieve full convention emergence (100% of the population in the same state/choosing the same action) in scale-free networks. Other researchers [Kittock, 1993; Shoham and Tennenholtz, 1997; Urbano *et al.*, 2009; Delgado, 2002; Delgado *et al.*, 2003] in the same topic and using the same type of topologies fixed their convergence rate to 90%, without considering (and informing the readers) that the rest 10% to achieve may not be possible to achieve, due to the presence of the identified SRSs. We have presented a composed social instrument as a robust solution against the persistence of subconventions in theoretical social networks, improving the convergence times obtained with simple rewiring and finally achieving full convergence.

In a world where almost 950 million users belong to online social networking platform (where virtual agents could also exist)[8], it is important to understand what mechanisms these virtual entities should be equipped with to facilitate the emergence of common conventions (for the sake of the whole group) as quickly as possible. Moreover, as a system manager, the results from this work highlights the harmful potential of Self-Reinforcing Structures within the network for delaying the emergence process, and draws our attention to solutions for such critical problems.

Acknowledgments

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[8]This report was accessed Sept 1st, 2010 at `http://www.comscore.com/Press_Events/Press_Releases/2010/8/Facebook_Captures_Top_Spot_among_Social_Networking_Sites_in_India`

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