Categorizing Social Norms in a Simulated Resource Gathering Society
(Work in Progress)

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Abstract

Our main interest research is focused on reaching a decentralized form of social order through the usage of social norms in virtual communities. In this paper, we analyze the effects of different sets of social norms within a society. The simulation scenario used for the experiments is a metaphor of a resource-gatherer prehistoric society. Finally, we obtain a qualitative ranking of all the possible sets of social norms in our scenario performing agent-based simulation.

Introduction and Related Work

Social norms are part of our everyday life. They help people self-organizing in many situations where having an authority representative is not feasible. On the contrary to institutional rules, the responsibility to enforce social norms is not the task of a central authority but a task of each member of the society. From the book of Bicchieri (Bicchieri 2006), the following definition of social norms is extracted: "The social norms I am talking about are not the formal, prescriptive or proscriptive rules designed, imposed, and enforced by an exogenous authority through the administration of selective incentives. I rather discuss informal norms that emerge through the decentralized interaction of agents within a collective and are not imposed or designed by an authority". Social norms are used in human societies as a mechanism to improve the behaviour of the individuals in those societies without relying on a centralized and omnipresent authority. In recent years, the use of these kinds of norms has been considered also as a mechanism to regulate virtual societies and specifically societies formed by artificial agents ((Saam & Harrer 1999), (Shoham & Tenneholtz 1992), (Walker & Wooldridge 1995), (Grizard *et al.* 2006)). From another point of view, the possibility of performing agent based simulation on social norms helps us to understand better how they work in human societies.

One of the main topics of research regarding the use of social norms in virtual societies is how they emerge, that is, how social norms are created at first instance. This has been studied by several authors ((Axelrod 1986), (Sen & Airiau 2007), (Gilbert 2002), (Kittock 1994), (Savarimuthu *et al.* 2007), (Excelente-Toledo & Jennings 2004)) who propose different factors that can influence this emergence. We divide the emergence of norms in two different stages: (a) how norms appear in the mind of one or several individuals and (b) how these new norms are spread over the society until they become accepted social norms. We are interested in studying the second stage, the spreading and acceptance of social norms, what Axelrod (Axelrod 1986) calls *norm support*. Our understanding of norm support deals with the problem of which norm is established as the dominant when more than one norm exists for the same situation. In the literature we can find several works ((Sen & Airiau 2007), (Kittock 1994)) that address with this problem, using a prisoner's dilemma as evaluation function, converting the problem of norm support in a coordination problem, where the agents have to learn to cooperate with the rest of the society, otherwise any kind of social punishment will be applied to them.

Our model, in contrast to those solving coordination problems, can deal with social norms that are not representable in a decision table and the rewards for following a certain norm are not known a priori. A similar approach can be found in the work of Cecconi and Parisi (Cecconi & Parisi 1998), where they also deal with a simulated resource consuming society. In their work, agents do not know beforehand how good the sets of social norms they follow are, even though the authors only consider two well differentiated sets of social norms (individual strategy or collective strategy of resource consumption). However, a society can have several (more than just two as we have already seen in the literature) sets of social norms abided by different members of the society. In the work of Sen (Sen, Biswas, & Debnath 2000), we observe that the authors present 6 different strategies (or sets of social norms), but they study the behaviour of mixed populations of these kinds of agents. Nevertheless, each of these sets of social norms, acting individually, can be of different quality with respect the society's goal. Therefore, it is useful to know beforehand the quality of a set of norms in a society, assuming that all the agents share the same set of social norms. In this paper we present a deep analysis of simulation results and the statistical techniques used **to establish a ranking of quality of all the possible sets of social norms** that members of a well-defined society can abide by. The assumption addopted is that all the members share the same set of social norms, with the hypothesis that, when agents find themselves in a socially mixed society, they will tend to a common set of norms, and such set of norms should be optimal. The research contained herein follows that performed by (Villatoro & Sabater-Mir 2007) where a genetic algorithm was the mechanism in charge of finding the most efficient set of norms in a given society. The main motivation (and part of future work) of this research is, once the quality of each different set of social norms is defined, to create simulations of heterogeneous societies. In these simulations agents will be loaded with different sets of social norms, and agents will be provided with the ability of changing their set of social norms. Therefore, we plan to observe a convergence of all the agents into a set of social norms. Our final goal is to study the mechanisms that favour that the final dominant set of social norms is the best in the ranking we have previously established. The article is structured as follows: firstly, we present the motivation of the problem and the inspiration we are using for the simulation scenario. Secondly, it is described the problem we deal with in this article, as well as the hipothesis. Subsequently all the details of the simulation model are specified. Thirdly, the experimental setting is introduced and the results of the experiments are analyzed. Finally, we draw some conclusions from the results obtained.

Reference Scenario

In order to design an scenario where the usage of social norms is significant, we are inspired by real life examples ((Paolucci, Conte, & Tosto 2006), (de Waal 1996)), where the usage of social norms is vital for the survival of the society. The society we use for our experiments is a resource-gatherer distributed and decentralized society. All the members of the society survive by consuming resources that appear randomly in the environment and exchanging the resources among them by **abiding to a set of social norms**. Depending on the quality of these social norms, the society succeeds in the task of increasing the average life expectancy of its members.

The application domain of this research is directly related to an ongoing research which is carried out by a group of archaeologists. We are presented a non-prehistoric society, already extinguished, known as *'the Yámanas'*. This society was located in Southern Argentina and are one of the groups of the societies commonly known as 'canoeros'. They lived there for around 6000 years in a very hostile environment. The main success, and reason of study, of this peculiar society is their ability of auto-organization: the *Yámanas* were able to auto-organize themselves as a hunter-gatherer society. The archaeologists consider as the hypothesis that the key of success in this society was due to their strong respect for a known set of social norms (represented as a set of myths). These social norms regulated, amongst other behaviours, the resource exchange between the *Yámanas*. From the study of Gusinde (Gusinde 1982), we extract that social norms for resource exchange regulation only made sense in such societies when the resources to be exchanged would appear sporadically although of a large contribution when they appear (e.g. finding a whale on the beach was a huge amount of resources but it would not happen frequently). Therefore, we adapt the parameters of the simulation to this scenario.

We want to stress that even though we inspired our simulations by the previously described society, the simulation scenario is a simplification of it. Consequently, we do not intend to affirm that the results obtained out of our simulations, as they are now, are directly applicable to real societies. Notwithstanding, the results have relevance for societies of virtual agents.

Statement of the Problem

The problem to be faced in the following sections is a study of the effects of each set of social norms within the society that uses them. We perform an exhaustive analysis of every possible set of social norms in our resource-gatherer society, forcing each time all the members to share the same set of social norms. This analysis provides us with the necessary information to **establish a classification of sets of social norms depending on their quality**. The quality measure used in our experiments is the Average Life Expectancy of the agents. Having fixed the ranking , we observe the characteristics that make a set of social norms optimal, with the intention of applying this characteristics to different scenarios in the future work. Our hypotheses are:

- **H1** - Different sets of social norms obtain different results on the quality measure we are using.
- **H2** - Environmental settings can affect the ranking of social norms.
- **H3** - Social norms promoting selfishness generate heterogeneous societies (as dictatorships).
- **H4** - Homogeneous societies are obtained with sets of social norms that promote empathy.

Simulation Model

We use a multi-agent system for our simulation. This multi-agent system is defined as an undirected graph: $MAS = \langle A, Rel \rangle$, where $\mathcal{A} = \{Ag_1, Ag_2, Ag_3, \ldots, Ag_n\}$ is a set of *n* agents representing the vertices of the graph, with $n \geq 1$; and *Rel* the set of relations (edges) between the agents. All the neighbours of distance 1 in the graph *MAS* of a certain agent is defined as the *neighbours network* of this agent. All the agents are initially loaded with 100 resource units. The simulation algorithm is based on a discrete step timing model, where each time step the algorithm observes the state and consequent actions of each agent before ticking another time step. Every time step, the simulation algorithm runs over every agent. The order in which the algorithm runs over the agents is randomly changed each time step. In this way all the agents are able to execute their actions, in a random order each time step, anulling any kind of advantage of one agent over the rest.

Each agent consumes one resource unit each time step as energy consumption for survival. When one agent exhausts its resources, it dies. After dying, agents are able to ressurrect with the initial resource conditions, after recalculating its *Average Life Expectancy* (ALE). This ALE is calculated by averaging the age of death plus the previous ALE. At the beginning of the simulation, all agents are loaded with an initial ALE of 100.

Firstly, in each time step, our algorithm evaluates (following continuous uniform probability distibution) if each of the agents have to find resources by observing the agent *Resource Gathering Probability*, that is defined as:

Resource Gathering Probability (P_{rg}) is ranked in the interval $[0, 1]$. P_{rg} specifies the probability an agent has to find resources each time step.

In case the algorithm evaluates that an agent has to find resources, the agent will receive a large amount of resources that can either use for its own consumption or for donating.

Secondly, in each time step, our algorithm evaluates if an agent has to meet another agent by observing the agent *Interaction Probability*, that is defined as:

Interaction Probability (P_{int}) is ranked in the interval $[0, 1]$. P_{int} specifies the probability of an agent to meet another agent connected to it.

In case the algorithm evaluates positively that an agent has to meet another one, it randomly chooses another agent from the agent's neighbours network. The interactions among agents are done always in pairs, and both agents have to choose an action when interacting. This decision is taken following the *set of social norms* that each agent has internalized. The set of norms specifies if the agent has to give or not give resources to the other agent, depending on both agent's resource levels. In order to formalize our concept of social norm, we first need to define several terms.

All agents can perceive a finite set of *observables* $\mathcal{O}$, and each element of the set is denoted as *ob*. Every agent also has a finite set of *actions A*, and each element of the set is denoted as *a*.

Every agent can find itself in a finite set of different *situations* $\mathcal{S}$, and each element of the set is denoted as $sit \subset \mathcal{O}$. In other words, a *situation* is a combination of different observables.

Given that, a **social norm** SN_i is a tuple formed by a situation and an action: $SN_i = \{\langle sit_g, a_h\rangle \mid sit_g \in \mathcal{S}, a_h \in A\}$.

In our scenario, the set of observables is formed by the following propositional terms: $\mathcal{O} = \{$ *Plenty(Me), Plenty(You), Normal(Me), Normal(You), Starving(Me), Starving(You)*$\}$, where: *Plenty(X)* indicates that *Agent's X* resource level is over 100 units; *Normal(X)* indicates that *Agent's X* resource level is between 25 and 100 units; and, *Starving(X)* indicates that *Agent's X* resource level is below 25 units. The values that X can take are *Me* and *You*, representing the acting agent and the partner agent in the interaction. When two agents meet, each agent is able to observe its own level of resources and its opponent level. The whole list of possible situations (formed by two observables) in which an agent may find itself can be seen in Table 1. The set of possible actions are $A = \{\text{Give Resources}, \text{Do not Give Resources}\}$. The combination of all possible situations associated to an action generates a **set of social norms**.

Each agent always abides by the set of social norms that it has internalized. When the social norm indicates to give resources, the agent has to decide the amount of resources it gives. Each agent has been provided with a *Donation Reasoning Process* that allows it to calculate the amount of resources to donate. The Donation Reasoning Process is the following:

Situation		**Action**
Starving(Me)	Starving(You)	To Give / Not To Give
Starving(Me)	Plenty(You)	To Give / Not To Give
Starving(Me)	Normal(You)	To Give / Not To Give
Plenty(Me)	Starving(You)	To Give / Not To Give
Plenty(Me)	Plenty(You)	To Give / Not To Give
Plenty(Me)	Normal(You)	To Give / Not To Give
Normal(Me)	Starving(You)	To Give / Not To Give
Normal(Me)	Plenty(You)	To Give / Not To Give
Normal(Me)	Normal(You)	To Give / Not To Give

Table 1: *Situations and Actions. Structure of a set of social norms.*

if $(Age_A \geq ALE_A)$ *and* $(Resources_A \geq PlentyLevel)$
then
  $Donation =$
  $SharingFactor \times (Resources_A - PlentyLevel)$
else
  $Donation = (1 - SharingFactor)^2 \times Resources_A$
end

Age_A corresponds to how old Agent A is. ALE_A refers to the Average Life Expectancy of Agent A. $Resources_A$ is the amount of resources that Agent A posses at that moment. *PlentyLevel* is the level in which the agent is considered to be plenty. And *SharingFactor* is a factor applied to donate a relative amount of the total. In the experiments studied herein this sharing factor is fixed on a 70%.

In other words, when an agent has more resources than what it needs to increase its average life expectancy, it donates more; when an agent do not have enough resources, it donates a smaller amount.

The donation reasoning process has been designed in such a way so that it fulfils the motivation of the scenario we are simulating that were introduced in previous sections.

Experiments and Results

Once the characteristics of the simulation platform have been grounded and the architecture of the agents is clear, we make use of them to test our theories of how efficient a set of social norms can be.

We suspect that depending on the amount of resources available in the environment, a different set of social norms will be the most efficient in every scenario, changing therefore the behaviour of the agents depending on the availability of resources.

Experiment Design

We need to test every single set of social norms over a society where every member of the society shares the same set of social norms. We have decided to load into the simulation a society with the following characteristics:

- The number of agents loaded in the simulation has been fixed to 90. This amount of agents allow us to approximate the society result to a normal distribution, so that it fulfills the central limit theorem.

- Fully Connected Neighbour Network: every agent is connected to all the other agents in its neighbour network.
- All the agents have the same Interaction Probability, and it has been fixed to $P_I(Agent_i) = 0.1$. This parameter is fixed to this value to avoid the continuous interactions among agents. A limited number of interactions makes the result of this interaction more important when happening. [1]
- All the agents have the same Resource Gathering Probability, and this parameter ($P_{RG}(Agent_i)$) is variable depending on the experiment.
- All the agents have the same set of social norms. Every possible set of social norms is loaded into the agents, executed and analyzed its effect after a period of time.
- When agents find resources, 250 units of resources are found. [1]

Apart from these parameters, we also have to specify the simulations parameters. All simulations are run for 250000 steps. In each simulation, a different set of social norms is loaded, until all possible sets of social norms have been executed. For each different set of norms, 20 simulations are run and certain parameters are saved. These parameters are: Average Life Expectancy of each agent, Standard Deviation of the Average Life Expectancies of the society, and Median Average Life Expectancy of the society.
As it was explained in Section *Simulation Model*, each agent could find itself in 9 possible different situations. In each of these situations, an agent always has two options: to give or not to give resources. Therefore, 2 *actions* raised to the power of 9 *situations* gives us a result of 512 different sets of social norms that will be studied separately.

Experiment 1

In this first experiment we have fixed $P_{RG}(Agent_i) = 0.0025$. This value indicates, for example, that in a grid world of 100 cells in each side, 25 cells (out of 10000) would be loaded with resources every time step. We consider it a *low* resource gathering probability, which do not allow the society to perpetuate. Therefore, we are interested in finding out which are the sets of norms that lengthen the average life expectancy of the society. After running an exhaustive test over all the possible set of social norms, we can observe the results in the following figure. The horizontal axis represents each one of the 512 possible sets of social norms. The vertical axis represents the mean of the median average life expectancy of the society from each of the 20 simulations.

H1 - Different sets of social norms obtain different results on the average life expectancy of the agents is verified with the results. In same environmental conditions, different sets of social norms produce different results in the agents average life expectancy. The society, notwithstanding the social norms used, does not get to perpetuate for the whole simulation in any of the simulations. Therefore we observe which sets of norms obtain the best results. In Figure 1, we can perfectly distinguish between three different levels:

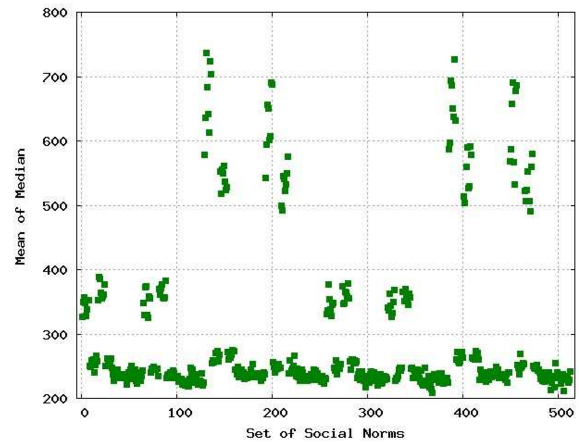

Figure 1: *Median Average Life Expectancy using different sets of social norms.* $P_{RG}(Agent_i) = 0.0025$

1. In the first level (median average life expectancy (ALE) lower than 300) we define the **Bad** sets of social norms.
2. In the second level (median ALE between 300 and 400) we define the **Average** sets of social norms.
3. In the third level (median ALE higher than 400) we define the **Good** sets of social norms.

In Figure 1, and in the levels aforementioned, we constantly refer to the mean of the median ALE. This median ALE represents information from only one member of the society, and does not provide us a with precise idea of how the rest of the society has behaved. It could happen that in two different societies with the same median ALE, the distance between the best and the worst member of the society was very different: one very large, representing a heterogenous society; and one very small, representing a homogenous society. In order to observe the homogeneity of each society, produced by the sets of social norms, we observe also the Average Standard Deviation of the simulations. If the Average Standard Deviation is low, this shall mean that all the agents have obtained similar results, obtaining consequently, an homogeneous society.

In Figure 2, we can observe four different data clusters:

- The lowest one (A) indicates a poor performance of these sets of social norms that this cluster holds. Although the bad performance of the set of norms in respect to the median average life expectancy of the society, it shows a very low standard deviation. The average median life of the agents is relatively low, but, so it is the standard deviation, which means that all the agents inside these societies obtain similar ALEs. The sets of norms in this cluster are tagged as **low**.
- The following one (B) shows an average performance. Inside this cluster it can be seen two smaller ones. One

[1]This value has been chosen to fulfil the reference scenario previously presented and obtained from (Gusinde 1982)

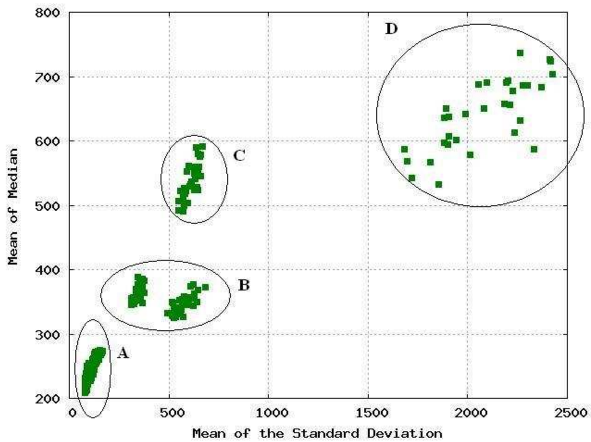

Figure 2: *Median Average Life Expectancy VS Mean of Standard Deviation.* $P_{RG}(Agent_i) = 0.0025$

of the smaller clusters represents more homogeneous (referring tothe resulting population) sets of norms than the other one, although the median life of the agents is average with respect to the rest of the social norms. The sets of norms in this cluster are **medium**.

- The third cluster (C) shows the sets of social norms that we define as **high**. Societies using these sets of norms obtain a good median ALE, similar (slightly smaller in this third cluster) to the best cluster. It also results in a more homogeneous society than the last one. The sets of norms in this cluster can be tagged as **high and homogeneous**.
- The last cluster (D) is the most dispersed one. Although the performance in the "Mean of Median" axis is the highest, it is also the cluster that shows a higher standard deviation. These sets produce societies in which the "median agent" obtains a very good ALE, although the rest of agents obtain very different values. Therefore we can state that the sets of norms in this cluster are **high but heterogeneous**.

The sets of norms that show a good (high) performance deserve a deeper study. Consequently we extract such sets of norms and analyze the characteristics of both high clusters (C and D).
The sets of norms obtained in the heterogeneous cluster are the ones with the following IDs: 128 - 135, 192 - 199, 384 - 391, 448 - 455.
Each of the sets of social norms corresponds to a complete table of situations and its corresponding action. For example, the sets of norms identified as 128 - 135 are represented in Table 3. In each of the columns we can identify the action that is associated to the corresponding situation: To Give Resources (G) or Not To Give Resources (N G).

The set of norms in Table 3 (128-135) can be simplified into a more generalized one. This generalization is done following the theories of Karnaugh maps. By observing the three middle rows, these correspond to the situations *Plenty(Me)* and all the three possible observables for *You*. Therefore, and pursuant to the theory of Karnaugh maps, we generalize that the corresponding action for the situations with the observable *Plenty(Me)* is always *Do not give*, without considering the *You* observables (regardless of the value thay may hold, result would not vary). In a similar way we generalize the last three rows, corresponding to the situations with the observable *Normal(Me)*. Finally, the first three rows, corresponding to the situations with the observable *Starving(Me)*, can be omitted. This is also done following Karnaugh maps theory. Since all possible combinations are covered, we can consider that that situation is not meaningful when extracting the generalization. The resulting generalization is:

If $Plenty(Agent_A)$ **Then** Do Not give Resources to $Agent_B$
If $Normal(Agent_A)$
If$Plenty(Agent_B)$ **Then** Give Resources to $Agent_B$
Else Do Not give Resources to $Agent_B$

By repeating the previous generalization procedure with the rest of sets of social norms, we obtain the following ("abstracted") sets of social norms:

1. **For the Sets of Norms (128-135):**
   If $Plenty(Agent_A)$ **Then** Do Not give Resources to $Agent_B$
   If $Normal(Agent_A)$
   If$Plenty(Agent_B)$ **Then** Give Resources to $Agent_B$
   Else Do Not give Resources to $Agent_B$

2. **For the Sets of Norms (192-199):**
   If $Plenty(Agent_A)$ **Then** Do Not give Resources to $Agent_B$
   If $Normal(Agent_A)$
   If ($Plenty(Agent_B)$ **or** $Starving(Agent_B)$) **Then** Give Resources to $Agent_B$
   Else Do Not give Resources to $Agent_B$

3. **For the Sets of Norms (384-391):**
   If $Plenty(Agent_A)$ **Then** Do Not give Resources to $Agent_B$
   If $Normal(Agent_A)$
   If ($Plenty(Agent_B)$ **or** $Normal(Agent_B)$) **Then** Give Resources to $Agent_B$
   Else Do Not give Resources to $Agent_B$

4. **For the Sets of Norms (448-455):**
   If $Plenty(Agent_A)$ **Then** Do Not give Resources to $Agent_B$
   If $Normal(Agent_A)$ **Then** Give Resources to $Agent_B$

Moreover, the generalization process can be performed on these resulting four generalized sets of social norms, obtaining just the last of the generalized set of social norms, since this one represents the most general situation. One conclusion that we may extract from this experiment is: when being an agent in resource-scarce environments, do not consider the others state, give only when you are normal and do not give when you are plenty of resources. This kind of norms promote the enrichment of those who are *Plenty*, favouring from those that continously die and ressurect, and not returning anything to the society. Thus, we have obtained a selfish society, but remembering that obtains good results although in an heterogeneous manner. Therefore, **H3**

Situation		Set 128	Set 129	Set 130	Set 131	Set 132	Set 133	Set 134	Set 135
Starving(Me)	Starving(You)	N G	G	N G	G	N G	G	N G	G
Starving(Me)	Plenty(You)	N G	N G	G	G	N G	N G	G	G
Starving(Me)	Normal(You)	N G	N G	N G	N G	G	G	G	G
Plenty(Me)	Starving(You)	N G	N G	N G	N G	N G	N G	N G	N G
Plenty(Me)	Plenty(You)	N G	N G	N G	N G	N G	N G	N G	N G
Plenty(Me)	Normal(You)	N G	N G	N G	N G	N G	N G	N G	N G
Normal(Me)	Starving(You)	N G	N G	N G	N G	N G	N G	N G	N G
Normal(Me)	Plenty(You)	G	G	G	G	G	G	G	G
Normal(Me)	Normal(You)	N G	N G	N G	N G	N G	N G	N G	N G

Figure 3: Sets of Norms 128-135

- Social norms promoting selfishness generate heterogeneous societies is confirmed.

We still have to analyze the homogeneous cluster. The norms extracted (following the same previous procedure) from the homogeneous-high cluster are the following:

1. **If** ($Plenty(Agent_A)$ **or** $Normal(Agent_A)$)

   If $Plenty(Agent_B)$ **Then** Give Resources to $Agent_B$

   Else Do Not give Resources to $Agent_B$

2. **If** $Normal(Agent_A)$

   If ($Plenty(Agent_B)$ **or** $Starving(Agent_B)$) **Then** Give Resources to $Agent_B$

   Else Do Not give Resources to $Agent_B$

   If $Plenty(Agent_A)$

   If $Plenty(Agent_B)$ **Then** Give Resources to $Agent_B$

   Else Do Not give Resources to $Agent_B$

3. **If** $Normal(Agent_A)$

   If ($Plenty(Agent_B)$ **or** $Normal(Agent_B)$) **Then** Give Resources to $Agent_B$

   Else Do Not give Resources to $Agent_B$

   If $Plenty(Agent_A)$

   If $Plenty(Agent_B)$ **Then** Give Resources to $Agent_B$

   Else Do Not give Resources to $Agent_B$

4. **If** $Normal(Agent_A)$ **Then** Give Resources to $Agent_B$

   Else Do Not give Resources to $Agent_B$

   If $Plenty(Agent_A)$

   If $Normal(Agent_B)$ **Then** Give Resources to $Agent_B$

   Else Do Not give Resources to $Agent_B$

On the other hand, these norms, in contrast to the heterogeneous norms, do pay attention on the other agents state to decide the action to take, confirming that **H4 - Homogeneous societies are obtained with sets of social norms that promote empathy**. Possibly, this refinement in the decision process is the cause of the homogeneity.

Experiment 2

In this second experiment we have increased the amount of resources by fixing $P_{RG}(Agent_i) = 0.004$. We consider it a probability where agents, depending on the efficiency of the set of social norms, can achieve a good performance. Therefore, in this experiment we pursue the same objective described in Experiment 1: to find which are the codes that lengthen the average life expectancy of the society. After running an exhaustive test over all the possible set of social norms, we observe the results showed in Figure 4.

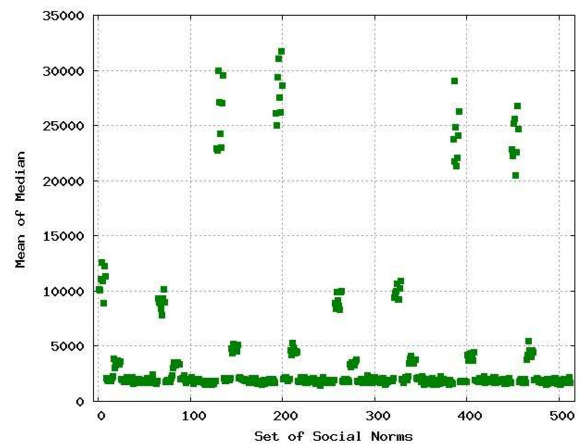

Figure 4: *Median Average Life Expectancy using different sets of social norms.* $P_{RG}(Agent_i) = 0.004$

In Figure 4, we can observe a similar pattern of the distribution of the results over the space search. Although the scale in the axis of mean of median is larger this time, we can observe three levels as well:

1. In the first level (median ALE lower than 6000), we identify the **Bad** sets of social norms.
2. In the second level (median ALE between 6000 and 14000), we identify the **Average** sets of social norms.
3. In the third level (median ALE higher than 14000), we identify the **Good** sets of social norms.

At this time we also study the results in terms of homogeneity. This can be observed in the following figure.

As it happened in the first experiment, in Figure 5 we can observe four different data clusters. This time, it is more difficult to affirm which of them is the best cluster with respect to the others. On the one hand we have sets (A and B) that obtain poor results on the "mean of median" scale, but with a very low standard deviation. On the other hand, we have the most dispersed cluster (D), which obtains the best results, although showing a very high standard deviation. Finally, the third cluster (C), which obtains lower results than the fourth one, despite also having a lower standard deviation. However, when compared to the second cluster, we can observe a significant raise in the standard deviation for a not much significant raise in the "mean of median" scale.

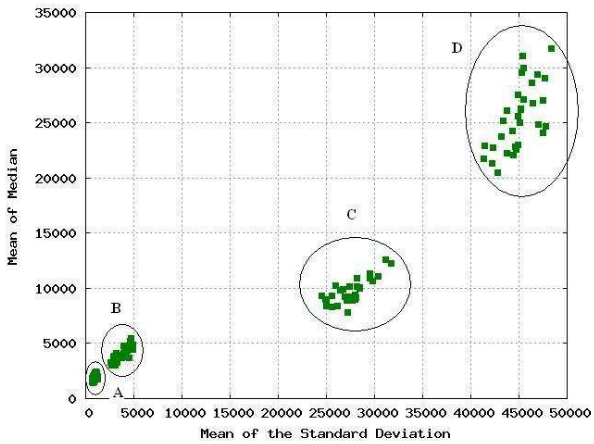

Figure 5: *Median Average Life Expectancy VS Mean of Standard Deviation.* $P_{RG}(Agent_i) = 0.004$

Accordingly, a decision has to be taken; sets of norms that produce: either the wealthiest society but with a high heterogeneity, or, a wealthy society (but not as wealthy as the previous one) but with a lower heterogeneity too.
Despite this discussion, we would also like to observe the norms producing the two highest clusters that previously we distinguished between homogeneous and heterogeneous.
The sets of norms obtained in the heterogeneous cluster are exactly the same that the ones obtained in the first experiment.
The sets of norms obtained in the homogeneous cluster are:

1. **If** $(Plenty(Agent_A)$ **or** $Normal(Agent_A))$ **Then** Do Not give Resources to $Agent_B$

2. **If** $Normal(Agent_A)$
   If $Starving(Agent_B)$ **Then** Give Resources to $Agent_B$
   Else Do Not give Resources to $Agent_B$
   If $Plenty(Agent_A)$ **Then** Do Not give Resources to $Agent_B$

3. **If** $Normal(Agent_A)$
   If $Normal(Agent_B)$ **Then** Give Resources to $Agent_B$
   Else Do Not give Resources to $Agent_B$
   If $Plenty(Agent_A)$ **Then** Do Not give Resources to $Agent_B$

4. **If** $Normal(Agent_A)$
   If $(Starving(Agent_B)$ **or** $Normal(Agent_B))$ **Then** Give Resources to $Agent_B$
   Else Do Not give Resources to $Agent_B$
   If $Plenty(Agent_A)$ **Then** Do Not give Resources to $Agent_B$

These norms are slightly different from those obtained in the first experiment. In these sets of norms, the *Starving* agents might still get some resources from other agents, while in the other example did not happen. These favouring to the *Starving* agents is due to the amount of resources; in this scenario is easier for the agents to find resources, therefore, makes sense to help them all. These differences confirm **H2 - Environmental settings can affect the ranking of social norms**. All the sets can be summarized into the last one. In these sets of norms we can still confirm the theory proposed at the end of the first experiment: to obtain a homogeneous society agents still have to pay attention on the other agents state to succeed.

Conclusions and Future Work

We have presented in this article a simulated society and an exhaustive study of social norms oriented to share resources that members of such society might use. From this analysis, we are now able to establish a quality scale of the different sets of social norms when acting separately. We can conlude that selfish behaviours promote the proliferation of dictatorships of resources (some agents holding the majority of resources without sharing them with the rest of the society), consequently obtaining an heterogeneous society. On the contrary, in order to obtain homogeneous societies, the sets of norms have to promote empathy (making agents share resources in an intelligent way).
In this article, we have assumed that all members of the society share the same set of social norms. This assumption cannot be made when trying to simulate a real-life environment where to apply social norms as it could be a peer-to-peer information market. In this kind of real problems, it might happen that each individual uses a different set of social norms. Once we know the qualities of all the possible sets of norms, we intend to study the mechanisms that make a certain set of social norms become the dominant and used by the vast majority of the members of a society. Special attention will be paid on reputation mechanisms as a mean to control fraudulent behaviours.

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References

Axelrod, R. 1986. An evolutionary approach to norms. *The American Political Science Review* 80(4):1095–1111.

Bicchieri, C. 2006. *The Grammar of Society: The nature and Dynamics of Social Norms.* Cambridge University Press.

Cecconi, F., and Parisi, D. 1998. Individual versus social survival strategies. *Journal of Artificial Societies and Social Simulation* 1(2).

de Waal, F. 1996. Good natured. *Harvard University Press*.

Excelente-Toledo, C. B., and Jennings, N. R. 2004. The dynamic selection of coordination mechanisms. *Journal of Autonomous Agents and Multi-Agent Systems.*

Gilbert, N. 2002. Varieties of emergence. Edited transcript of the introductory talk given at the Workshop on Agent 2002 Social Agents: Ecology, Exchange, and Evolution Conference.

Grizard, A.; Vercouter, L.; Stratulat, T.; and Muller, G. 2006. A peer-to-peer normative system to achieve social order. In *AAMAS' 06 Workshop on Coordination, Organization, Institutions and Norms in agent systems (COIN)*.

Gusinde, M. 1982. *Los Indios de la Tierra del Fuego*. CAEA.

Kittock, J. E. 1994. The impact of locality and authority on emergent conventions: initial observations. In *AAAI'94 Proceedings of the Twelfth National Conference on Artificial Intelligence*, volume 1, 420–425. American Association for Artificial Intelligence.

Paolucci, M.; Conte, R.; and Tosto, G. D. 2006. A model of social organization and the evolution of food sharing in vampire bats. *Adaptive Behavior* 41(3):223–239.

Saam, N. J., and Harrer, A. 1999. Simulating norms, social inequality, and functional change in artificial societies. *Journal of Artificial Societies and Social Simulation* 2(1).

Savarimuthu, B. T. R.; Cranefield, S.; Purvis, M.; and Purvis, M. 2007. Role model based mechanism for norm emergence in artificial agent societies. In *Proceedings of the AAMAS'07 Workshop on Coordination, Organization, Institutions and Norms in Agent Systems (COIN), Honolulu, Hawaii, USA*.

Sen, S., and Airiau, S. 2007. Emergence of norms through social learning. *Proceedings of IJCAI-07* 1507–1512.

Sen, S.; Biswas, A.; and Debnath, S. 2000. Believing others: Pros and cons.

Shoham, Y., and Tenneholtz, M. 1992. On the synthesis of useful social laws for artificial agent societies (preliminary report). In *Proceedings of the AAAI Conference*, 276–281.

Villatoro, D., and Sabater-Mir, J. 2007. Norm selection through simulation in a resource-gathering society. In *Proceedings of 21st European Simulation and Modelling Conference (ESM)*.

Walker, A., and Wooldridge, M. 1995. Understanding the emergence of conventions in multi-agent systems. In Lesser, V., ed., *Proceedings of the First International Conference on Multi–Agent Systems*, 384–389. San Francisco, CA: MIT Press.