Evolutionary game theory for the synthesis of norms

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Abstract

Societies usually require the existence of norms that regulate the actions of their members in order to achieve a good behaviour. For instance, humans have developed jurisprudence as the theory and philosophy of law to regulate the behaviour of their society. Following this objective, we would like to investigate whether we can take an evolutionary approach to assess the norm(s) that would help to a group of agents to achieve their goals without conflicts between them. The used scenario to evaluate our proposal is a traffic-oriented one, where agents are cars that have to traverse a road junction. Empirical evaluation of this system leads to results that tell us how norms are good to regulate an multi agent system that simulates a car society, letting the cars go to a better situation, collisionless, with norms than without them.

Keywords: Evolutionary algorithms, Multi-Agent normative systems, Evolutionary norm synthesis.

1. Introduction

Autonomous agents and norms emergence in Multi-Agent Systems (MAS) constitute an alternative approach to design complex systems. Norm emergence is a popular norm generation method in MAS, where agents interact among them in a scenario to experiment with the results of their actions and learn in an unsupervised way. Eventually, agents may reach a common behaviour. In this work we do not do norm generation, we study how to evaluate norms in a Multi-Agent System by means of Evolutionary techniques based on agents previous experience of a set of norms.

Our work starts from a previous study of norm generation of the scenario we are going to use (J. Morales and Vasconcelos, 2013), the aim of this study was to generate norms and make the agents of the simulation (cars) capable of reasoning and applying this norms. In our case, we are going to adapt the previous work incorporating an evolutionary approach (Phels and Wooldridge, 2013) to know whether a group of intelligent individuals evolve in a norm regulated system to avoid conflicts, and if the evolution is positive experiment with a different pool of norms and see if the evolution lets to the best norms, for this society, "live" and the worst "die".

In section 2 we describe the architecture of this previous work and the tool used to create it, section 3 describes our implementation and used evolutionary approach for the norm synthesis, the realized experiments and their results are explained in section 4 and finally we give some conclusions and future work in section 5.

2. Background

The basic background to understand how we made this work are the next ones: Repast Simphony and a traffic simulator that is made with this tool.

2.1. Repast Simphony

Repast Simphony (Repast Simphony, Argone National Laboratory)(*Recursive Porous Agent Simulation Toolkit*) is a free and open source agent-based modeling toolkit that simplifies model creation and use. Repast allows the user to create Multi-Agent System systems and run simulations to study how agents interact. It incorporates a rich variety of tools to build models and study the results of the simulations, such model component development, flowcharts, modeling and visualization of 2D and 3D environments, a concurrent multithreaded discrete event scheduler, libraries for genetic algorithms, neural networks, regression, random number generation, and specialized mathematics, and more.

2.2. Traffic Simulator

In this work, we have adapted a car simulator (done with Repast Simphony) that simulates a road junction where the agents are cars and are going from a starting point to a destination point. When a car enters to the scenario by being disposed in one of the four entry points, it chooses a random destination point to get of the map. We can see the traffic simulator scenario in Figure 1.

As we can observe, the scenario is a grid with a road junction in the middle of it, the road direction is represented with the arrows, the starting points are the black circles and the destination points the red circles.

The part of the scenario that is visible from the point of view of a car is called CarScope, and consists of a MxN matrix where, by default, M = 1 and N = 3. Each cell of the matrix represents the positions in front of the car, as depicted in Figure 2.

Having into account the cars knowledge of the world, their scope, we can generate the structure of norms they are going to understand. A norm will be composed of a condition and an action; the condition will be a scope that the agents could perceive, represented by $\{<, >, \wedge\}$ equal to {car heading left, car heading right, car in your same direction} and the condition in this traffic case would be to stop ($prh(go)$).

For example, we could have a norm forcing to stop a car if the scope of the same is of {car heading right, nothing, nothing} represented as $\{>, -, -\}$. Also, exists a symbol to express that what it is in that cell doesn't matter, this symbol is $\{*\}$. So, if we have a norm of $\{>, *, *\}$ means that no matter what is in the cell of the middle and of the right that if

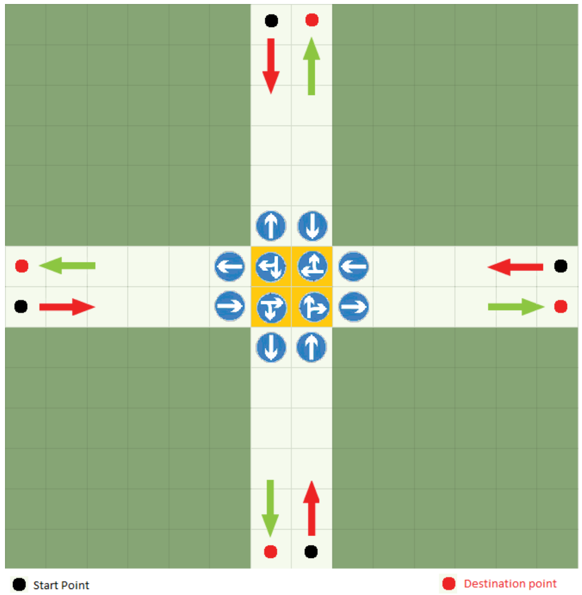


Figure 1: The intersection map

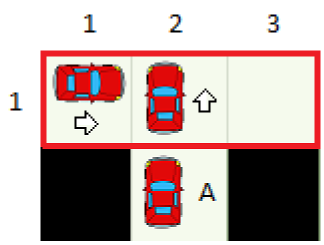


Figure 2: Scope of the car A, marked with a red line

we have in the left side a car heading right we have to stop, this would be the norm that gives way to left (like in the real world driving method).

3. Evolutionary approach

The idea is to use an evolutionary approach to norm synthesis, taken this traffic scenario to prove the necessity of norms. We start with a scenario populated by a group of agents, each using one of a pool of possible norms or non. When the simulation runs, the cars will act with the inherited norms until a certain number of time steps (ticks) has passed. After this ticks we will compute the success of the norms for the last time step and then evolve the scenario by asexual reproduction. We will create a new scenario in which an agent adopts a norm with a probability that is determined by how successful that norm was compared to the others. So, if a particular norm n_1 is twice as successful at avoiding crashes as another norm n_2, then an agent is twice as likely to adopt n_1 than n_2:

$$\begin{aligned} P_{Norm1} &= (P_{Norm1} * 2/(P_{Norm1} * 2 + P_{Norm2} * 1) \\ P_{Norm2} &= (P_{Norm2} * 1/(P_{Norm2} * 1 + P_{Norm1} * 2) \end{aligned} \tag{1}$$

In this way the norm population has evolved in the population. Over time, we will look to see which norms survive and prosper. A fitness characteristic of a norm is simply the extent to which the use of that norm allows an agent to achieve its goals without crashes. The fitter a norm is, the more likely it is to prosper over time, in an evolutionary sense.

The fitness of a norm used by an agent is computed with a formula that given a norm n used by agent a, its fitness $f_a(n, T)$ after a time period T is assessed as follows:

$$f_a(n, T) = (k * s_T) - (\alpha * k * (j_T - s_T)) \tag{2}$$

Where j_T are the number of journeys of agent a during T, s_T stands for the number of successful journeys (journeys without collisions that allowed the agent reach its destination) during that period, $\alpha > 0$ is the penalization degree for crashing and $k \geq 0$ is a reward factor. The first part of the fitness function accumulates rewards for successful journeys, whereas the second part penalizes agents that do not reach their destination because they crashed.

4. Empirical evaluation

We now perform an empirical evaluation of the evolutionary approach to norm synthesis for the traffic scenario described in section 2. We first detail in section 4.1 the empirical settings of our experiments. Thereafter, in section 4.2 we empirically show that the evolutionary approach is capable of synthesising the best norms for cars, evolving to the norms that avoid conflicts.

4.1. Empirical settings

Our experiments employ the simulator described in section 2 to simulate a traffic scenario. As initial experiments we consider different populations composed of 10 agents that model the cars of this scenario. The experiments are going to be divided in two groups:

- Agents aware of a **norm vs** agents **without norms** knowledge.
- Agents with the knowledge of a **norm vs** agents with a knowledge of **another norm**.

The fitness function described in section 3 will be computed every 100 time steps (ticks) and afterwards, asexual reproduction will occur: each agent chooses a norm with the probabilities computed to each norm in the fitness function. The simulation will terminate when either a maximum number of 30.000 steps is reached or the system stabilises. The stabilisation criterion will be achieved when either all the population has choose the same norm or when in the last 100 time steps there where no collisions between cars.

First of all, we will consider the following norms to make the experiments. This pool of norms was synthesised with IRON (J. Morales and Vasconcelos, 2013) in the used traffic scenario, we can see them in the table 1:

Norm	Pre-condition	Modality	Semantics
n_1	$left(car\ heading\ right)$	prh(go)	Give way to left
n_2	$right(car\ heading\ left)$	prh(go)	Give way to right
n_3	$left(nil)$ & $front(nil)$ & $right(nil)$	prh(go)	Stop when there's no car at sight
n_4	$left(>)$ & $front(>)$ & $right(>)$	prh(go)	Give way to left (generalised by n_1)

Table 1: Pool of norms.

The selection of the above pool of norms is motivated as follows:

- n_1 $\{>, *, *\}$ and n_2 $\{*, *, <\}$ are norms that are expected to separately work well. However, we know that together they don't.
- We know that n_3 $\{-, -, -\}$ is a norm that will slow down cars and prevent them from reaching their destinations. It is a **bad** norm.
- n_4 $\{>, >, >\}$ is a particular case, and hence generalised by norm n_1. It applies in far less situations that n_1.

As we divided the experiments in two groups we consider the next **scenarios**:

- **Scenario 1: Norm vs No norm.** The pool of norms has just 1 norm n_1. Cars will employ either n_1 or no norm at all. We guess that in this scenario give way to left is evolutionary stable, meaning that it is worth having norms.
- **Scenario 2: Norm vs Norm.** The pool contains 2 norms. For example: n_1 vs n_2 and we would like to know whether one norm is better than the other, meaning that only with a norm the population can converge or that two norms can not coexist together.

For this scenarios we will run different experiments changing the population percentage and the penalization degree α that takes part in the fitness function.

The experiments will be distributed as follows:

1. Low penalty, $\alpha = 1$.
    - Population separated in 5 distributions: {(90,10);(70,30);(50,50);(30,70);(10,90)}
2. Medium penalty, $\alpha = 5$
    - Population separated in 5 distributions: {(90,10);(70,30);(50,50);(30,70);(10,90)}
3. High penalty, $\alpha = 10$
    - Population separated in 5 distributions: {(90,10);(70,30);(50,50);(30,70);(10,90)}

4.2. Empirical results

We know analyze the results of our empirical evaluation. First, we will perform the analysis of the relevance of the norms in a traffic scenario. Thereafter, we will perform the analysis of a norm against another.

4.2.1. Norm relevance

Our first analysis is focusing in the relevance of the norms in a traffic scenario, where some cars are aware of norms and others are not. With this experiments we want to assure that the usage of norms is worthy and a given population works better, arises a convergence (without collisions), with norms.

For this first set of experiments, we have used a population of 10 cars in which the population aware of the norm changes from a set of experiments to another and also the penalization degree of the fitness function, as we discuss in section 4.1. The evolution of the norms is done every 100 ticks, so the cars will choose the norms thanks to the probability computed by the fitness function.

The tables of the experiments shown below are the aggregate of 10 simulations, the first row describes the percentages of norm aware (n_{aware}) vs no norm aware ($\not{n}_{aware}$), wrote as: $n_{aware}/\not{n}_{aware}$. And the second row express the percentage of the cases in which the norm evolve and was accepted by the cars.

90/10	70/30	50/50	30/70	10/90
100%	100%	80%	70%	40%

Table 2: Experiment set norm vs no norm $\alpha = 1$.

90/10	70/30	50/50	30/70	10/90
100%	100%	90%	80%	60%

Table 3: Experiment set norm vs no norm $\alpha = 5$.

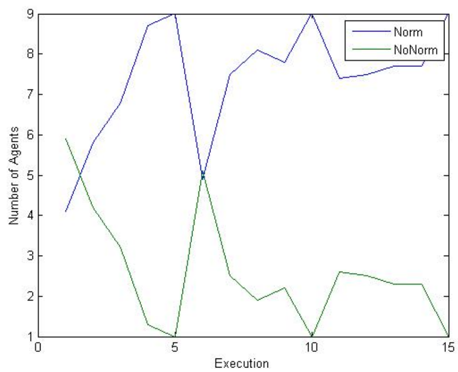
90/10	70/30	50/50	30/70	10/90
100%	100%	100%	100%	90%

Table 4: Experiment set norm vs no norm $\alpha = 10$.

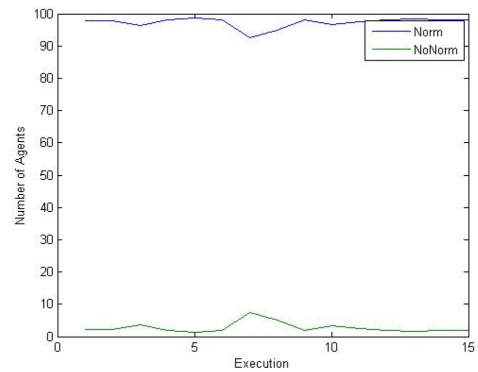
As we can see in the experiment tables above the collision penalization degree is a very important factor that will affect to the convergence of our system because its the value that penalizes the collisions that we wanted to avoid. However, we can notice that in the majority of the cases the evolutionary approach carry the population to a norm aware situation.

The worst case we could see is the one that only a 10% of the population is norm aware and only in the 40% of the cases the population evolve to a norm aware situation.

We performed the experiments a second time with a increased amount of agents. This time we used 100 cars instead of 10 and to give them more time to perform actions, the fitness function got executed every 300 ticks (instead of 100 ticks with 10 cars). It turned out the output is more stable than before. Even the before so critical 10/90 starting population with a penalty (α) of 1 get's with these new parameters 100% of convergence to norm aware populations. At the contrary than in the previous experiments in this one there was not a single experiment that ended up with a non-norm aware situation convergence.

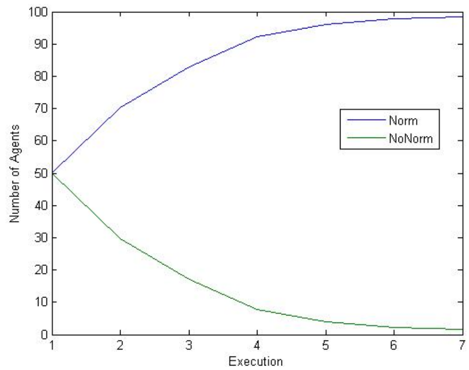


Experiments with 10 Agents

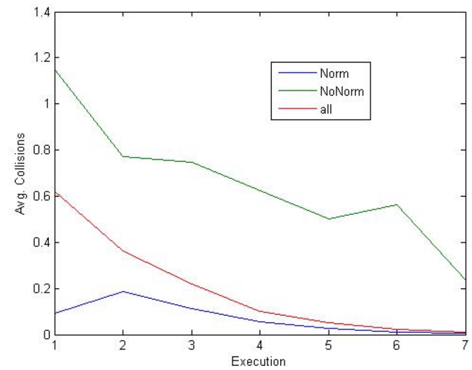


Experiments with 100 Agents

Each Experiment consists of 10 runs. We calculated the average last iteration population of these runs of all the 15 experiments. These can be seen in the two graph above. The first five executions of the experiments were executed with a $\alpha = 1$, the sixth to tenth execution with $\alpha = 5$ and the eleventh to fifteenth with $\alpha = 10$. The starting population of the first execution was 10/90, the second 30/70, the third 50/50, the fourth 70/30, the fifth 90/10. The sixth began with 10/90 again and so on. We can see that the experiments with 10 cars depend more on the alpha and starting population whereas the 100 car is more or less constant.



Agent / Iteration graph with $\alpha = 10$ and population 50/50



Collision / Iteration graph with $\alpha = 10$ and population 50/50

The graphs above show the Iterations during one run. Each Iteration corresponds to a call of the fitness function. This is one run of the $\alpha = 10$ and starting population 50/50 experiment. We can see a continuous switching of the population to the norms on the left figure. The right figure shows us the average collisions in total (no percentage) depending on the current iteration. The average collision decreases and aligns to the collisions of he norm aware agents.

With this results, we can say that the norm-aware systems are better than non norm-aware once to reach to a convergence status, where the collisions between agents are avoid. So, now we are going to compute the relevance of a specific norm against another one to know if a norm is better than other one.

4.2.2. Specific norm relevance

To test the performance of two different norms we performed the experiments using the second experiment parameters since we recognized a more reliable output with a increased amount of agents. Also we knew that comparing two norms is more complex which leads us to increase the amount of ticks required to perform the fitness function to 500.

In this second experiment we are comparing the norms n_1 and n_2, described in section 4.1 table 1, to know who is evolutionary better and avoids better conflicts in this specific scenario.

For a better comprehension of the results of these experiments we are going to express them in the tables below by showing the percentage of convergence of each of the norms for different populations. The populations are shown in n_1/n_2 so, for example, the first one would be 90% of the population aware of n_1 and 10% of the population aware of the n_2. Moreover, we have added a row of tie, because there are moments in which the two norms arrive to a stable situation in which together avoid conflicts.

norm	90/10	70/30	50/50	30/70	10/90
n_1	90%	60%	30%	10%	0%
n_2	10%	30%	20%	90%	100%
tie	0%	10%	50%	0%	0%

Table 5: Experiment set n_1 vs n_2, $\alpha = 1$.

norm	90/10	70/30	50/50	30/70	10/90
n_1	60%	30%	30%	10%	20%
n_2	30%	50%	50%	90%	80%
tie	10%	20%	50%	0%	0%

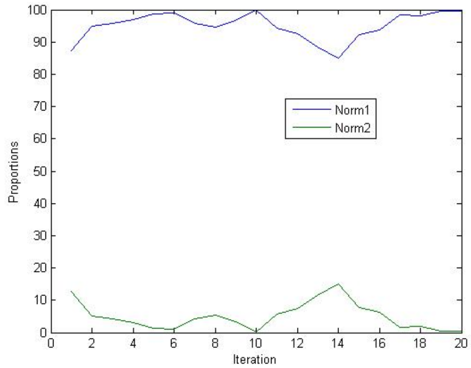
Table 6: Experiment set n_1 vs n_2, $\alpha = 5$.

norm	90/10	70/30	50/50	30/70	10/90
n_1	80%	30%	20%	0%	0%
n_2	10%	60%	70%	80%	80%
tie	10%	10%	10%	20%	20%

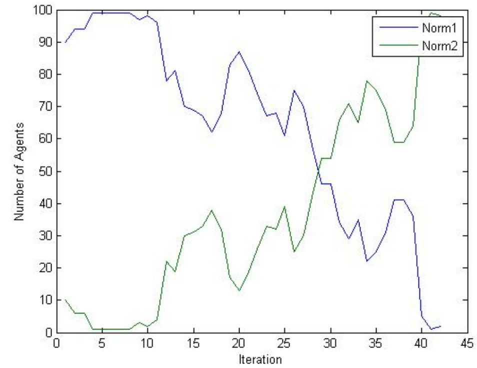
Table 7: Experiment set n_1 vs n_2, $\alpha = 10$.

As we see in the tables above, one for each grade of penalization (1, 5 and 10), we can notice that the norms are good and no one is better than the other, because when they are majority between the population they tend to avoid conflicts better than the other. This means that the two of them avoid conflicts in the society, but if we look more concisely we can notice that the norm n_2 is better than norm n_1, because in some situations in which n_1 is majority the population converges with the other norm and is not so clear on the other way.

Also we can notice that there are moments in which the norms get to a convergence status with the half of the population using a norm and the other half with the other one (this ones are shown in the *tie* row). This makes stronger the assumption that we make telling that the two norms are good ones.

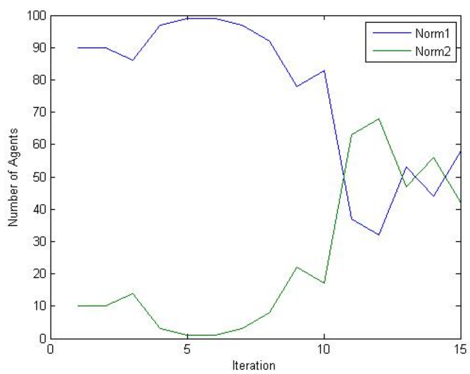


Convergence of Norm 1

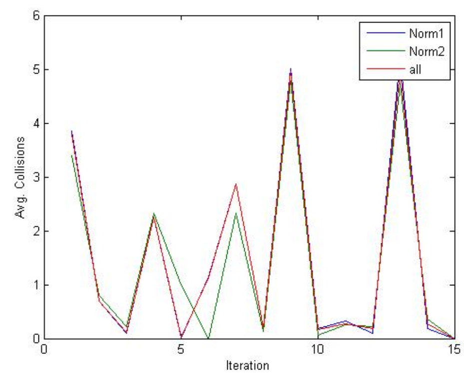


Convergence of Norm 2

In the above graphs we can see the the Convergence of Norm1 and Norm2 with an $\alpha = 1$ and a starting population of 90/10.



Convergence of both Norms



Convergence of both Norms - Collisions

The graph above shows the convergence of both Norms. The Collision graph shows us how the collisions get minimized and both Norms avoid collision.

5. Conclusions and Future Work

In this work we have investigate whether we can take an evolutionary approach to asses the norms that would help to a group of agents to achieve their goals without conflicts between them. We have presented first a traffic simulator that provides us the MAS scenario for our approach. Second we have described the process that we follow to evolutionary choose a norm thanks to a fitness function we create. Then we made some experiments to empirically demonstrate that norms are useful to regulate a community and that help to avoid conflicts. Finally, we also made experiments to demonstrate whether a norm can be better than other to regulate a society.

In this last step we obtained that the two norms computed are relevant in the cases that they are majority on the population and when they are equal the results lead to tie, however the norm n_2 seems to be more reliable than the norm n_1. But as we know the norms semantics and we know that the two of them are complementary norms (one gives way to left, whether the other one gives way to right), so this could make that the randomness of the cars travels has evolve to a norm that in other simulation could evolve to the other one.

Also, the empirical analysis make us notice of an important factor that is the penalization degree. A high degree will be most likely to converge to a non conflictive situation. Moreover, we have another value of relevance that is the time we let to the simulator run until we evolve to a new norm proportions. When the time step number is higher we are going to have more examples to know if a car with a norm (or no norm) was conflictive or not.

Finally, as future work we could make a new set of experiments with the population divided into different norms and different groups, more than the actual two. Also, an interesting experiment would be the combination of norms into groups of agents. The meaning of this experiment is to combine norms because maybe a norm is not relevant alone but could be very useful combined with another norm, or a set of norms.

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