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Impact of Communication on Agent-Based Social Simulations Using the PAX Framework

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***Abstract*—This paper investigates the impact of agents' communication on social simulations using the PAX framework. Previous works investigated the impact of structuring elements (*e.g.* houses, hospitals, roads, etc) on agents' behaviors. This work extends that, by investigating the combined results of different communication schemes and structural costs. To assess the plausibility of application of these ideas on real world problems, we modeled a small Brazilian town and scenarios of dengue fever spreading over its tiny population. Results show the relevance of communication on the overall population dynamics; combined results also reveal some curious social epiphenomena.**

***Index Terms*—Agent-based social simulations, Population dynamics, Intelligent agents, Multiagent systems, Social structures, Disease dissemination.**

I. Introduction

Social scientists have encountered in computer simulations a new kind of method for scientific investigation in Social Sciences. The possibility of modeling and simulating artificial societies, as well as analyzing particular social aspects and problems, is not essentially different of traditional methods, since computer models are equivalent to the mathematical ones in terms of phenomena representation. The main advantage of computer simulations is that they can incorporate mathematical models, while providing plausibility and abstraction.

Some mathematical models have been proposed as attempts of capturing the essence of human social behavior. However, the majority of these models are not always based on true premises. Works like those of John von Neumann and Oscar Morgenstern in Game Theory [1] provide important insights on the understanding of human collective strategies, but the assumption of perfect rationality is evidently false. Human social behavior reveals a bounded rationality.

Simulations of social phenomena are known as social simulations, and they are referred as agent-based social simulations (ABSS) when humans are represented by agents [2]. The major motivation to use agent-based models is the possibility of modeling and controlling different granularity levels, namely, the social global level and also the individual level. This advantage enables the researcher to produce highly heterogeneous and sophisticated kinds of virtual societies. Epstein and Axtell have shown strong arguments supporting the use of ABSS instead of analytical models [2].

Social simulations —and ABSS specifically— have supported the study of many social contexts and associated phenomena, such as egoism *vs.* altruism [3], reputation mechanisms [3]–[6], leadership-based coercive contexts [3]–[5], [7], social segregation [3]–[5], [8], culture transmission, spread of features across population (*e.g.* diseases) [5], [9], etc. The research field evolved greatly since Neumanns self-replicating machines and cellular automata (CA) to recent works in cognitive agent-based social simulations [10].

Many simulation platforms, toolkits, frameworks and models have been proposed to support ABSS, *e.g.* the Schellings segregation model [8], Garbage Can model [11], Sugarscape model [2], Vidya platform [3]–[5]. Not to forget the applications of swarm-based intelligent approaches.

In a previous work the authors presented the PAX (Plausible Agents matriX) framework, exploring the impact of social structuring elements (*e.g.* houses, hospitals, roads, etc) on agents behavior in ABSS [9]. The main purpose framework is to facilitate the incorporation of social structuring elements in the environment and in the agents beliefs system, as well as provide communication mechanisms.

ABSS environments may be classified according to three requirements for which they shall provide support, regarding relationships among simulation entities: (*i*) behavioral, (*ii*) temporal and (*iii*) spatial relations [12]. Traditional approaches often tackle well the behavioral and temporal requirements, but not the spatial specification of social structures. This is one of the main critics appointed by social theorist when discussing social simulations and ABSS [13]. The PAX framework addresses suitably all three requirements.

In this paper we assess the impact of communication mechanisms on the overall simulation, also analyzing the combined effects with structural costs. As case of study, we modeled a small Brazilian town in the Northeastern state of Pernambuco with approximately 12,000 habitants plagued with dengue spreading over its tiny population. Results show the impact of adopting different communication mechanisms in conjunction with spatial reconfigurations, reaveling a great applicability to epidemic dynamics modeling and control.

This paper is organized as follows: section 2 gives an overview on the ABSS research field; section 3 explains the PAX framework; section 4 demonstrates how the dengue fever dissemination was modeled and simulated; section 5 shows the simulation results; and section 6 concludes the paper.

II. Agent-Based Social Simulations

Social simulations is a young field of research. Besides this, many important tools were already proposed aiming to support social scientists in their investigations, linking social phenomena to computational models. Three good possible reasons for carrying out agent-based social simulations are: (*1*) possibility of likely prediction of future social outcomes; (*2*) easy test-bed for implementing social hypothesis; and (*3*) emergence leading to discovery of unknown relationships and principles.

We can attribute the principles of social simulations to the seminal studies of John von Neumman and Oscar Morgenstern on Game Theory [14]. Later, the Neumann's model of self-replicating machines motivated him to develop the first cellular automata (CA) model, giving the first steps in the direction of ABSS. When we are talking about cognitive agents, by equating agents to cells in a CA may override the principles of emergence of complex patterns from very simple rules. However, CA can improve significantly ABSS by representing another important mechanism of dynamics for interacting with or be part of the cognitive agents (*e.g.* disease spreading can be successfully modeled by CA).

The economist and Nobel laureate Thomas Schelling published in 1971 a paper (entitled "Dynamic Models of Segregation") in which it is explained how racial dynamics happens based on individual neighborhood preferences considering race [8]. Technically, the Schelling's segregation model is a kind of CA, since global patterns (racial segregation) arise from local rules (small individuals' racial neighborhood preferences). In 1972, Michael Cohen *et al.* developed the Garbage Can model [11].

Based on the model of self-replicating cellular automata, John Conway put foward the Game of Life, demonstrating graphically that simple rules can produce highly complex global patterns. This work influenced a new generation of population-based algorithms, like the Boids developed by the computer graphics expert Craig Reynolds, used to simulate flocking birds. ABSS became an established research field with the works of Joshua Epstein and Robert Axtell in the development of the first general purpose ABSS model, the Sugarscape [2]. The model has been used to simulate social, economic and biologic phenomena, explicitly based on agents. More recently, Ron Sun proposed the adoption of cognitive agents' architectures to support ABSS, influencing a new generation of highly plausible cognitive social simulations [10].

In 2006 and 2007 the authors were involved in the development of the Vidya multi-agent systems platform, initially posed as a god-game with agents whose actions are devised through evolutionary computation [4], but used later as a test-bed for ABSS, exploring social human-like behaviors (*e.g.* egoism *vs.* altruism [3]) and simulating spread of diseases over populations in unstructured and primitive virtual worlds [5].

In a recent work the PAX framework was introducing, demonstrating the impact of structuring elements on agents' behaviors in social simulations [9]. The focus of PAX is on the development of highly structured social simulations and plausible agents' models. It incorporates intuitive mechanisms to approximate real environments, and provide good abstractions to human agents and global dynamics.

III. The PAX Framework

PAX is an ABSS framework developed with the Java programming language (JDK 6). The framework architecture was conceived to give support to ABSS in the specification of the following elements:

1) *Environments* — definition of structures, structural levels and environment cells' labels;
2) *Entities (or objects)* — the basic elements of simulations, defined by a set of spatial characteristics;
3) *Entities' interaction interfaces* — defines the entity's set of actions that others entities can produce on it;
4) *Agents* — abstract structures to implement context-specific agents.

A. Environments

PAX environments are 2-dimensional matrices specified by three types of elements: structural levels; structuring elements; environmental cells' labels. Each structure in PAX is an entity with spatial coordinates (placement), dimensions (*i.e.* width and length) and may also contain others structures alike inside it. The disposition of structures inside an environment affords and can influence the adoption of different agents' strategies, functioning as instruments that promote global order, as well as creating beneficial contexts that impact on the dynamics of social networks.

B. Entities

Entities are anything conceivable to be included in an environment. They have spatial coordinates (2-dimensional), a meta-location (*i.e.* the structures it is located, or no structure) and an entity interaction interface. Thus, the Entity class is the basic class of the whole simulation. It is used when the user (*i.e.* the social scientist) want to create context-specific objects. This is done only implementing some abstract methods and providing an entity interaction interface (if necessary).

C. Entities' Interaction Interfaces

Entities' interaction interfaces are made of rules that guide the way entities of the simulation world interact each other. For this, an entity interface incorporates a set of possible actions that other entities can perform over the entity and a entity state, on top of which restrictions will be placed based on the current state of the entity. Therefore, when the PAX experimenter is designing an object and needs to include restrictions on its behavior during interactions with other entities, he may only need to implement an entity interaction interface.

D. Agents

PAX agents are entities designed to be intelligent. Nevertheless, the framework does not supply any particular implementation of intelligent components for agents' behavior. However, PAX provides an abstraction for perception and action, leaving the responsibility of intelligent processing on the developer's hand. Therefore, the user, when implementing a specific kind of intelligent agent, has to build an intelligent module that maps perceptions to actions.

IV. CASE STUDY

In a previous work we have used the PAX framework to simulate a fictitious environment to investigate the impact of structuring elements' placement on agents' behaviors [9]. In that environment, we simulated an epidemic dynamics considering some scenarios, aiming to assess all yield impact.

Regarding the modeling of environments, this work innovates in relation to the previous one in the following aspects: (*a*) scales-up to representation of a real town; (*b*) incorporate representation abilities of a real disease (*i.e.* dengue fever); (*c*) allows many more agents; (*d*) incorporates several distinct communication schemes among agents.

A. Simulation of the Iguaraci City

We have simulated Iguaraci, a small Brazilian town located in the Northeastern state of Pernambuco. Real data was collected from the Pernambuco state official database (http://www.bde.pe.gov.br) (BDE-PE) and the Brazilian Institute of Geography and Statistics (IBGE) (http://www.ibge.gov.br/english). Iguaraci has an area of approximately 780 km^2 and a population of approximately 12,000 habitants, leading to a demographic density of 15 hab/km^2.

In the simulated environment, we mapped Iguaraci as a grid of square cells of cardinality 28×28, each cell abstracting 1 km^2. Based on the real layout of the town, we divide it in 4 communities —2 large (22 hab/km^2) and 2 small (5 hab/km^2). As we are simulating dengue dissemination over the population, we placed in the environment health structures, *i.e.* hospitals and health stations. *Iguaraci* has 1 hospital and 3 health stations, but these structures are not sufficient to attend all its health demand. Hence, the population has to use health services of two neighbor towns: *Afogados da Ingazeira* and *Sertania*. For this reason, 2 additional hospitals were considered, representing the Hospital of *Afogados da Ingazeira* (19 km away) and the Hospital of *Sertania* (46 km away). The two towns are linked to *Iguaraci* by the state road PE-292. These elements are all illustrated in Figure 1.

All data from the abovementioned sources was collected in the beginning of the 2007 year. We assumed that each agent in the simulation perform 5 actions in one day, thus the simulated day has 5 iterations. Total simulated time period was 910 iterations, meaning 6 months in the real world.

B. Communicating Agents

In the environment were added 4 agents' communities, totalizing 12000 simulated agents. Each agent has an "infection" label and a "wellbeing". The infection label informs if the agent is infected by dengue and the other, if the agent is feeling good or sick, regardless of being infected or not. However, if the agent is infected, it always feels sick. What guides an agent

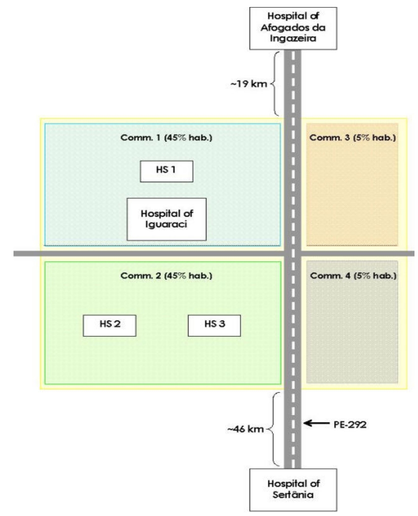

Fig. 1. Illustration of the simulated *Iguaraci* town elements (HS mean health station).

to any available health unity (*i.e.* hospital or health station) is the "wellbeing" label (*i.e.* the sensation of being sick), not the knowledge of being infected. This is a hedonistic perspective, as most humans naturally subscribe to it.

Some of the agents' actions need locomotion. For those there is a cost proportional to the distance to be covered and terrain difficulty. Here, we assumed 4 possible scenarios: (*i*) with good roads, the cost is only the distance; (*ii*) without roads (clear terrain), the cost is penalized by a factor of 10.0; (*iii*) without roads (challenging terrain), penalization factor is 20.0; (*iv*) without roads (rough terrain), penalization factor is 30.0. This means that migration has to consider route costs.

In the beginning of simulations, agents do not know the best actions to perform for each state. As simulations progress, agents learn through reinforcement learning aiming to tune-up their behavior to their particular needs, considering their current states. An agent state is a combination of its current location and feeling. The possible locations for an agent to be are: Community 1; Community 2; Community 3; Community 4; Hospital of *Iguaraci*; Hospital of *Afogados da Ingazeira*; Hospital of *Sertania*; Health station 1; Health station 2; and Health station 3. The possible feelings are "feeling good" and "feeling sick". For each state there is a set of possible actions that can be performed by an agent. The possible actions, considering all states, are the following: go to community 1; go to community 2; go to community 3; go to community 4; go to hospital of *Iguaraci*; go to hospital of *Afogados da Ingazeira*; go to hospital of *Sertania*; go to health station 1; go to health station 2; go to health station 3; walk inside community; go home; and, do nothing.

Agents can communicate with each other. The knowledge transmission between two agents is referred here as local communication. In local communication, agent share knowledge about the best options of actions to be performed in the location they are. We have not added any kind of reputation mechanism, thus agents do not differentiate agents. Also in local communication, agents share information about how to fight the dengue causes (*i.e.* eliminating water pools). We have also added a broadcast communication mechanism, meaning for example government health campaigns to instruct segments of the population on how to fight dengue. So, there are four possible communication scenarios: (*1*) without any form of communication among agents; (*2*) only local communication among agents; (*3*) only global communication (*i.e.* broadcast); and (*4*) including both, local and global communication.

C. Dengue Dissemination Dynamics

Since the dengue is a vector-borne disease, the dissemination cycle in the proposed model is based on the mosquito-human-mosquito (mainly *Aedes aegypti*) infection cycle. Agents are infected via bites of vector mosquitoes [15]. The mosquitoes' infection is due to one of following events: (*i*) if a mosquito bites an infected agent (*i.e.* horizontal transmission); (*ii*) if it is descendant from an infected female mosquito (*i.e.* vertical transmission). This is the case as only female *Aedes aegypti* are hematophagous [15]. In our model, the proportion of mosquitoes able to bite the agents is 50%. In this model, the intrinsic and extrinsic virus incubation period was abstracted. All those parameters can be included later.

The disease dissemination cycle was subdivided in: (*1*) hatching of the eggs —the eggs hatched in one iteration is proportional to the number of eggs and the rate of water inside the cell (of the grid); (*2*) infection propagation —the mosquitoes will bite the agents and infect them. If a healthy mosquito bites an infected agent, the mosquito will become infected and from now on the infection will be transmitted to all its offspring; (*3*) mosquitoes dispersal —since each cell is an abstraction of 1 km^2 of the town area and an *Aedes aegypti* can fly up to 100 m of distance [16], some mosquitoes will eventually fly to a neighbor cell. The number of mosquitoes which will move from a cell to another was defined as a function of the cell area (*i.e.* 1 km^2), the population of mosquitoes in the cell and the maximum distance a mosquito can fly; (*4*) oviposition —due to the fact that the female *Aedes aegypti* needs a blood meal and water to lay its eggs, the number of new eggs is a function of density of agents, rate of water and number of female mosquitoes in the cell.

The dengue disease was simulated following a CA-like dynamics. Therefore, *Aedes aegypti* mosquitoes were not represented as agents, but abstracted in each cell of the environment by its quantity and the percentage of infected mosquitoes. Other variable values were hard-coded for each cell: the number of eggs, the percentage of infected eggs and the level of water in that cell. These values were initialized equally for all runs and changed over time as the simulation progress based on neighborhood and presence of agents. Although hard-coded, most of these simulation variables could be obtained should a more precise simulation was needed. This reinforces our point as offering PAX as a powerful simulation tool for social problems such as this.

V. Experiments and Results

A. Experimental Setup

The combination of different communication schemes and structural costs produced 16 simulated scenarios in total. The main objective of the carried out experiments was to verify the impacts of the different communication schemes on agents' emergent behaviors using the PAX framework as modeling and simulation tool.

The population performance was measured by its health and the capability of health units to attend infected agents. Aproximately 1% of agents were initialized as infected[1]. To build a more realistic environment relative to public health services, 10% of population per iteration was induced to feel sick, generating extra demand to hospitals in addition to the infected agents demand.

Each hospital can have different waiting queues limit and different (fixed) numbers of beds. The number of beds determines the number of agents that will be attended per iteration. Here all simulated hospital has an attendance queue of 50 agents. The Hospital of *Iguaraci* has 16 beds; the Hospital of *Afogados da Ingazeira* has 96 beds; the Hospital of *Sertania* has 55 beds. Health stations have also attendance queue of size 50, but only 1 bed each.

Other parameters were: global communication reaches 60% of population per iteration; a "conscientious" agent —an agent instructed to eliminate water pools— removes 5% of water present in water pools in every location it visits; only 1% of agents are initialized as still instructed to combat dengue; and in local communication, agents communicate with 1% of agents inside the same cell.

Each simulation represents a real period of one semester (182 days) and was inspected every 7 days (*i.e.* one data gathering per week). Simulations were carried out using an Intel® Core™ 2 Quad q6600 64 bits (*i.e.* 4 cores of 2.4 GHz) processor with 4GB of RAM. Each simulation lasted approximately 1h, and the results were averaged over 10 distinct runs.

B. Simulation Results

The first simulations aimed to investigate the influence of communication mechanisms and transportation facilities in the number of attendances in health units. We have observed that the scenarios with roads, but without any kind of agents' communication, have in general the worst results (*i.e.* greater number of attendances in units). This is illustrated in Figure 2, which shows the number of infected agents attended by the Hospital of *Afogados da Ingazeira* over time for the scenario with roads and different communications mechanisms.

Notice that the global communication (*i.e.* the preventive propaganda of dengue fever) in the scenario shown in Figure 2 has little importance if it is not combined with local communication. In all scenarios, local communication revealed to be extremely important in reducing attendance in hospitals, which

[1]Actually, this is a probabilistic value, since we have initialized each agent with probability 1% of being infected.

can be seen as a reduction in the number of infected agents. This can be clearly seen in Figure 3.

Figure 4 shows an interesting phenomenon: in a scenario with multiplication factor cost equals to 10.0, the combination of local and global communication gives in general the best results. This probably happens because agents can trade-off between transportation costs and disease costs, choosing to this particular scenario to stay at home even when infected.

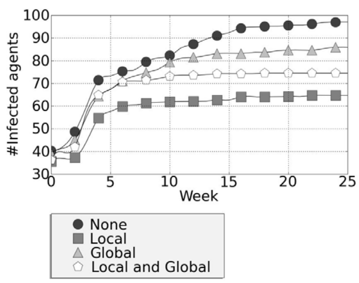

Fig. 2. Number of infected agents attended in the Hospital of *Afogados da Ingazeira* over time for the scenario with roads and different communications mechanisms.

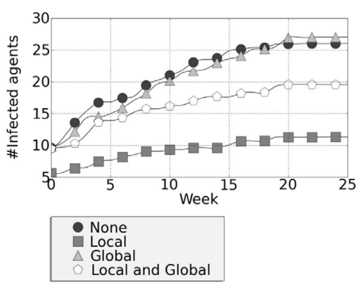

Fig. 3. Number of infected agents attended in the Hospital of *Iguaraci* over time, for the scenario without roads (multiplication factor cost of 30.0) and different communications mechanisms.

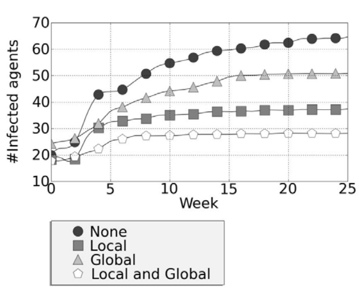

Fig. 4. Number of infected agents attended in the Hospital of *Sertania* over time, for the scenario without roads (multiplication factor cost of 10.0) and different communications mechanisms.

Overall, the number of attendances in health units is commonly proportional to the number of beds available.

Notice that the average attendance number is greater on the Hospitals of *Afogados da Ingazeira* and *Sertania* (96 and 55 beds, respectively) if compared to *Iguaraci* (16 beds).

As regarding Health stations, they have a much lower number of attendances (one bed only).

We have also observed that the percentage of infected individuals per community, correlating this with adopted communication schemes. Results were not also so intuitive as they reveal that communities closer to the Hospital of *Iguaraci* have healthier citizens if communication is disabled. These counter-intuitive results —because one would intuitively believe that communication enhance learning and learning speed by knowledge sharing— shows that wrong multi-agent learning can also be amplified through intensive communication. Figure 5 shows the "bad" influence of communication at community 1.

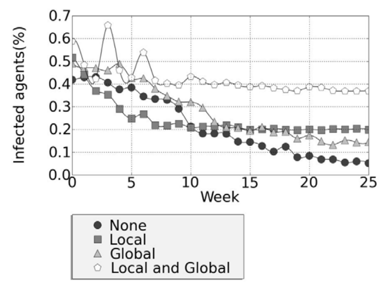

Fig. 5. Percentage of infected agents in community 1 over time, for the scenario with roads and different communications mechanisms.

The unusual behavior observed in Figure 5 is not the case in all runs, since correct learning also happens and communication becomes, as it should be, a positive characteristic. In general, the larger the transportation cost the lesser the influence of communications on wrong multi-agent learning. Another interesting phenomenon that happened in some scenarios was the relative good benefits of global communication to the society when distance to hospitals is large. This is especially interesting in community 2, because it is not so distant from hospitals (in relation to communities 3 and 4), but sufficiently distant to show extreme performances to local communication and global communication. This can be seen in Figure 6. Note that findings such as these might be very useful in real situations, *e.g* for government officials.

The third set of experiments aimed to investigate the influence of each health unit on the population health, considering different communication schemes and transportation costs. The results show that when communication is disabled the influence of placement of units is very important, but when communication is enabled placement has little influence; again, an interesting epiphenomenon. The percentage of attendance in the Hospital of *Iguaraci* presents an curious phenomenon when only local communication is enabled. The explanation could be related to the relative low cost for going to the town Hospital (much lower that all the others), so that even applying maximum penalty, agents still prefer to go to it. Again, the wrong effect of local communication was observed at times amplifying the learning to discard the good option of going to it. All this can be seen in Figure 7.

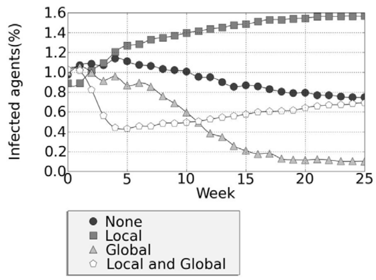

Fig. 6. Percentage of infected agents in community 2 over time, for the scenario without roads (multiplication factor cost equals to 30) and different communications mechanisms.

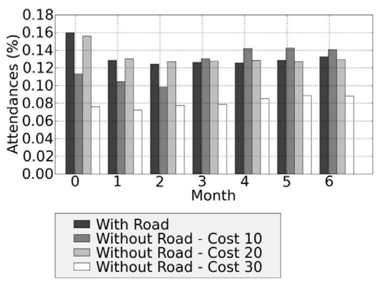

Fig. 7. Percentage of attendances in the Hospital of *Iguaraci* over time, for the scenario with local communication and for different transportation costs.

VI. Conclusion

In this paper the authors have investigated the impacts of communication mechanisms and its combined influence with placement of structures and transportation costs on agents' behaviors in social simulations. The PAX framework was used and proved itself very useful as modeling and simulation tool.

The case study selected was dengue fever spreading in a Brazilian small town. Real data was used to produce a plausible simulated environment for study of emerging dengue dynamics. The number of agents ($\approx 12,000$) per simulation in quite complex combination of factors proved that the PAX framework not only is a flexible tool, but also presents good performance.

Learning of agents was carried out by reinforcement learning drawn from interaction between agent and others world entities, including other agents (communication). Regarding to the explored communication mechanisms, agents were allowed to communicate with each other locally, while receiving global broadcast to learn how to fight dengue. Scenarios with different combinations of the mentioned communication mechanisms were explored.

Results on this regard have demonstrated the high importance of communication mechanisms in the whole agent population dynamics. When combined with different transportation costs and observed from different placement perspectives (*e.g.* from a distant hospital) the population dynamics reveals interesting emergent behaviors, some of which counter-intuitive (Figure 5).

Overall results reinforce the appropriateness of the PAX framework in performing agent-based social simulations. The authors argue that social scientists may profit greatly by using the presented framework, as it is able to incorporate behavioral, temporal and spatial relations among all entities of the simulated environment, as well as to provide different agents' communication mechanisms.

We argue that PAX and simulations presented in this paper can be useful on public policies planning in health care and other governmental fields. Future works should investigate the (*i*) influence of hyper-geometry of structural elements of the environment on agents' behaviors in the society and (*ii*) how more plausible simulations could be produced.

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