Break with agents who listen to too many others (at least when making Boolean decisions!)

(Extended Abstract)

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ABSTRACT

In multiagent scenarios where decision-makers have to coordinate actions (e.g., minority and congestion games), previous works have shown that agents may reach coordination mostly by looking at past decisions. Not many works consider the structure behind agents' connections. When structure is indeed considered, it assumes some kind of random network with a given, fixed connectivity degree. The present paper departs from this approach mainly as follows. First, it considers network topologies based on preferential attachments (especially useful in social networks). Second, the formalism of random Boolean networks is used to allow agents to consider their acquaintances. Our results using preferential attachments and random Boolean networks show that an efficient equilibrium can be achieved, provided agents do experimentation. Also, we show that influential agents tend to consider few inputs in their Boolean functions.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*Multiagent Systems*

General Terms

Algorithms

Keywords

Multiagent Systems, Self-organizing System, Minority Game, Traffic Simulation

1. INTRODUCTION

In multiagent systems, agents often face binary situations that require *coordination among the agents*. In minority games, previous works have shown that agents may reach appropriate levels of coordination, mostly by looking at the history of past decisions. Not many approaches consider any kind of structure of the network, i.e. how agents are connected. When structure is indeed considered, it assumes some kind of random network with a given, fixed connectivity degree. The present paper departs from the conventional

approach in three main ways. First, it considers more realistic network topologies, based on preferential attachments [2]. This is especially useful in social networks. Second, the formalism of random Boolean networks is used to help agents to make decisions given their attachments (for example acquaintances). This is coupled with a reinforcement learning mechanism that allows agents to select strategies that are locally and globally efficient. Third, for the sake of illustration we use two different scenarios that differ greatly in the way the reward function is structured, namely the El Farol Bar Problem (EFBP, a kind of minority game) [1], and an iterated binary route choice scenario (adapted from [5]), henceforth referred as IRC. With this approach we target systems that adapt dynamically to changes in the environment, including other adaptive decision-makers.

Minority games have been the focus of many works. Regarding the general idea, the most similar works to the present paper have appeared in [4] and in [3]. In these cases, a kind of social network was considered. However, the connectivity was such that the average number of neighbors with whom each agent interacts was fixed. In the present paper we use a topology with preferential attachment, which basically means that a few nodes have big connectivity while the majority of the nodes are connected to just another node.

2. METHODS

Here we use RBN's to equip the agents with a decision-making framework. RBN's are made up of binary variables. N agents form a network and each must decide which binary action to perform. Each agent is represented by one of these binary variables. These in turn are, each, regulated by some other variables, which serve as inputs. The dynamical behavior of each agent, namely which action it will execute at the next time step, is governed by a logical rule based on a Boolean function. These functions specify, for each possible combination of K input values, the status of the regulated variable. Thus, being K the number of input variables regulating a given agent, since each of these inputs can be either on or off (1 or 0), the number of combinations of states of the K inputs is 2^K. For each of these combinations, a specific Boolean function must output either 1 or 0, thus the total number of Boolean functions over K inputs is 2^{2^K}. When $K = 2$, some of these functions are well-known (AND, OR, XOR, NAND, etc.) but in general there is no obvious semantics. More details and a simple example of this regulation process can be found in [3].

By using RBN's, in the EFBP for instance, we replace the space of possible strategies described in [1] by a set of

Boolean functions. This also means that each node is connected to a given number of others. Hence, instead of having a random strategy, each node has random Boolean functions and uses them to determinate whether or not to go to the bar. Similarly, in the IRC scenario, instead of using a probabilistic approach to select a route (as in [5]), each driver agent explores a set of functions and a set of connections to other agents in order to make the route decision.

Each agent $i \in \mathcal{N}$ is a node in a random Boolean network and is connected to K_i others (notice that K hence may vary from agent to agent). Another parameter of the model is the number of functions each node possesses, $|\mathcal{F}|$.

Given the nature of minority games, the utility is highly coupled with the efficiency at system level. Efficiency is a domain-dependent concept related to the equilibrium of the particular system. In the EFBP the equilibrium calls for the bar accommodating ρ agents (in the original work $\rho = 60\%$). In the IRC, the equilibrium is such that route M carries $\rho = \frac{2}{3}$ of the traffic. Therefore agents must adapt and find functions that are efficient, i.e., provide high utility. Our approach for adaptation of the functions that are used at local level is based on an ε-greedy exploration process. At time step $t = 0$ one function from the set of $|\mathcal{F}_i|$ is assigned to each i. Then, at each further time step, the node decides to change the current function with probability φ. In case of a change, a new one is ε-greedy selected based on the utility it has provided so far. In the beginning of the simulation $\varepsilon = 1$ to allow exploration, but every time a function is changed, the value of ε is multiplied by $\delta < 1$.

According to f_i and to the value of the K_i entries, either 0 or 1 is output. In the EFBP scenario 0 means the agent stays at home; 1 means go to the bar. In the route choice scenario 0 and 1 mean the agent selects the main route (M) or its alternative respectively.

So far we have introduced the basic procedures, where each node has fixed connections, i.e., the set of K_i acquaintances does not change with time. Next, a variant called *change worst* (CW) is described. The CW variant is more utilitarian but also more realistic, in the sense that now agents evaluate the quality of their acquaintances. In the real-world, if someone is not performing well in the game, it will be likely to be labeled a black sheep and will be less and less considered as a part of a group (even if its bad performance may not be directly related to others). Thus, in this variant, each i looks at the reward r_j of each j it is connected and finds the agent with the worst reward. Let j^- be this agent. Agent i then marks j^- as a candidate for replacement, meaning that if i finds a better friend, it will no longer consider the action of j^- when deciding its own action. To replace j^-, i will look for a better connection among the best friends of its friends. Let j^+ be this agent. This does not affect j^+ since the relationship is not bidirectional. j^- however becomes less popular while j^+ increases its popularity and influence. In this process some nodes turn highly influential.

3. EXPERIMENTS AND RESULTS

The experiments performed (each repeated 30 times) consider the following values for the mentioned parameters: the horizon of simulation is $t_{max} = 1000$ time steps; $N = 900$ in both scenarios (this was the experimental setting in [5]); $|\mathcal{F}| = 10$; $\varphi \in \{0.1, 0.2, 0.9\}$ and $\delta \in \{0.999, 0.99, 0.9\}$.

In the case of the EFBP the main metric to be analyzed is

the amount of agents ρ that go to the bar (as in [1] in which $\rho = 60\%$). In the IRC, for $N = 900$ agents, the reward function is balanced in a way that an equilibrium for the distribution of reward occurs when 600 agents select M. In the CW variant, besides these two metrics for each domain, we have also performed microscopic analysis about how the topology of the network changes (details of this dynamics available on demand). We do this aiming at understanding the role of degree in the reward of the agents, as well as the degree distribution in the efficiency of the whole system.

Due to lack of space we do not show the plots but notice that in the case in which K_i does not change, in both the EFBP and the IRC the system efficiency is reached (the time taken depends on values of the parameters, especially φ). In the CW variant, we notice that the convergence to the efficient action selection now takes more time, due to the fact that not only functions change in the CW case but also the connections. We have also conducted microscopic analysis, whose conclusion is that more influential nodes tend to be simple (low K), probably because, having less functions to try, they are more foreseeable, thus making the adaptation to them (by the neighbors) easier.

4. CONCLUSION

As it is common in minority and congestion games, instead of assuming knowledge about the history of the interactions, in the present paper we assume that agents interact in a social network. In particular, differently from previous works, the connectivity degree K is not homogeneous. Rather, agents are connected based on preferential attachment. We then let each agent i decide which action to do based on a Boolean function that maps the inputs of K_i acquaintances to i's output. Our approach admits some variants that were tested, as for instance whether or not to exchange acquaintances. We have found that using our approach, each agent is able to select an action that brings the system to the equilibrium, thus achieving the implicit coordination already observed by other authors. Moreover, using agent-based simulation, we are able to study microscopic properties such as how the influences change within time. The main finding is that more influential nodes tend to be simpler, i.e., have few inputs only.

5. REFERENCES

[1] B. Arthur. Inductive reasoning, bounded rationality and the bar problem. Technical Report 94–03–014, Santa Fe Institute, 1994.

[2] A. L. Barabasi and R. Albert. Emergence of scaling in random networks. *Science*, 286(5439):509–512, 1999.

[3] Daniel Epstein and Ana L. C. Bazzan. Decision making using random Boolean networks in the El Farol Bar Problem. In *Proc. of the Agent-Based Simulation (ABS / ECMS 2011)*.

[4] Aram Galstyan, Shashikiran Kolar, and Kristina Lerman. Resource allocation games with changing resource capacities. In *Proc. of the Second International Joint Conference on Autonomous Agents and Multiagent Systems*, pages 145–152. ACM Press, 2003.

[5] F. Klügl and Ana L. C. Bazzan. Route decision behaviour in a commuting scenario. *Journal of Artificial Societies and Social Simulation*, 7(1), 2004.