Role of information and topology in agent-based competitive systems with limited resources

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Abstract

The problem of competition, cooperation and the emergence of collective behaviour in the presence of limited resources is quite general, and one of cornerstones of evolutionary dynamics both in the natural and in the artificial worlds. These models exhibit complex phenomena, governed by various parameters that describe the quantity and the quality of agents involved. We study how these parameters influence the efficiency of the models, measured as efficient distribution of limited resources, and how the additional information like vicinity, it's structure, the number and the cognitive abilities of participants modify these models. We extend the classical prototype of such environment, i.e, minority games, by allowing agents to process additional information originating from local minority games that involve the neighbourhood of the agent considered.

Minority games

Minority games (MG) constitute a simple multi-agent based approach for the simulation of financial markets. It was first introduced by Challet and Zhang in [1]. Although it has been mainly used to simulate financial markets, with certain modifications this model can be used to simulate other systems where agents act independently and in their best interest, while the resource for which they are competing is limited.

The model of the minority games is based on the El Farol Bar problem, defined by Brian Arthur in [2].

The model is defined as a set of N agents, where N is an odd integer. The population of the agents is involved in a series of repeated games where at each round every agent has to make a choice between two actions. Each agent makes his decisions based on a set of deterministic strategies that are available to him. The agents on the minority side win the round.

The sum of all the agent's decisions is called the attendance, denoted as A(t) and its variance defines the volatility fo the system that we want to optimize.

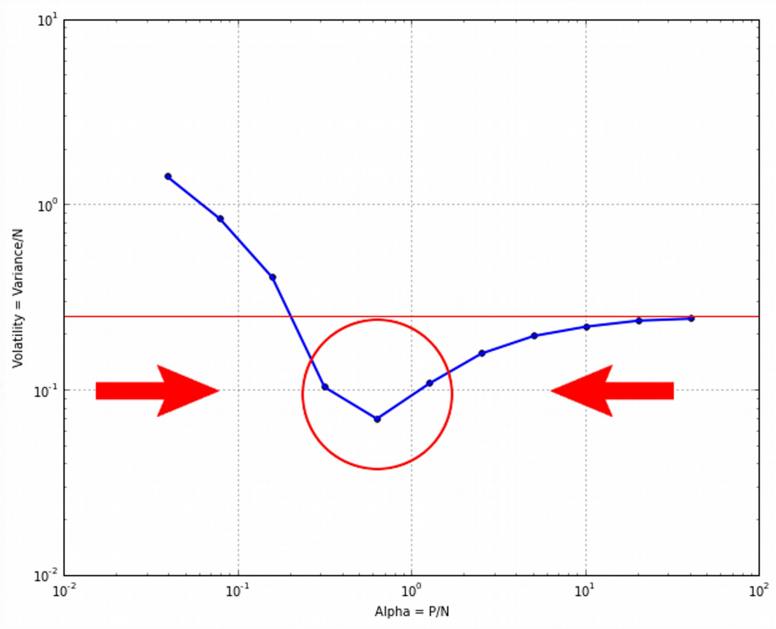


Figure 1: Normalize variance versus control parameter α

A major feature of the MG model are the two distinctive phases which characterize the game with different collective behaviour explained by the agents quantity and cognitive abilities.

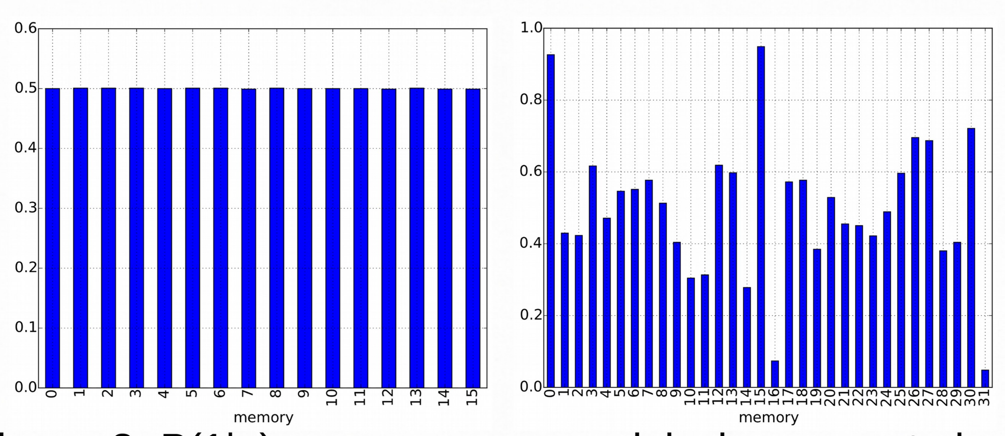


Figure 2: P(1|μ) versus μ on a model where agents have M = 4 using a sliding window of length 4 and 5

The symmetric and the asymmetric phase are also called unpredictable and predictable. In the symmetric phase it is more convenient to play in a random fashion, while in the asymmetric a cooperation emerges.

Topology of the model and vicinity information

In the basic model of minority games all agents act independently without the ability to communicate with each other. The only means of passing information between them is by using the history of the model that encapsulates all the decisions made by agents in a string of bits.

Once the information of the neighbouring agents is added to the model, two important factors start to influence the dynamics of the system, (i) the dimension of the vicinity, ie. the quantity of neighbouring agents and (ii) the topology of the network. We have tested various topologies which made possible the communication between agents.

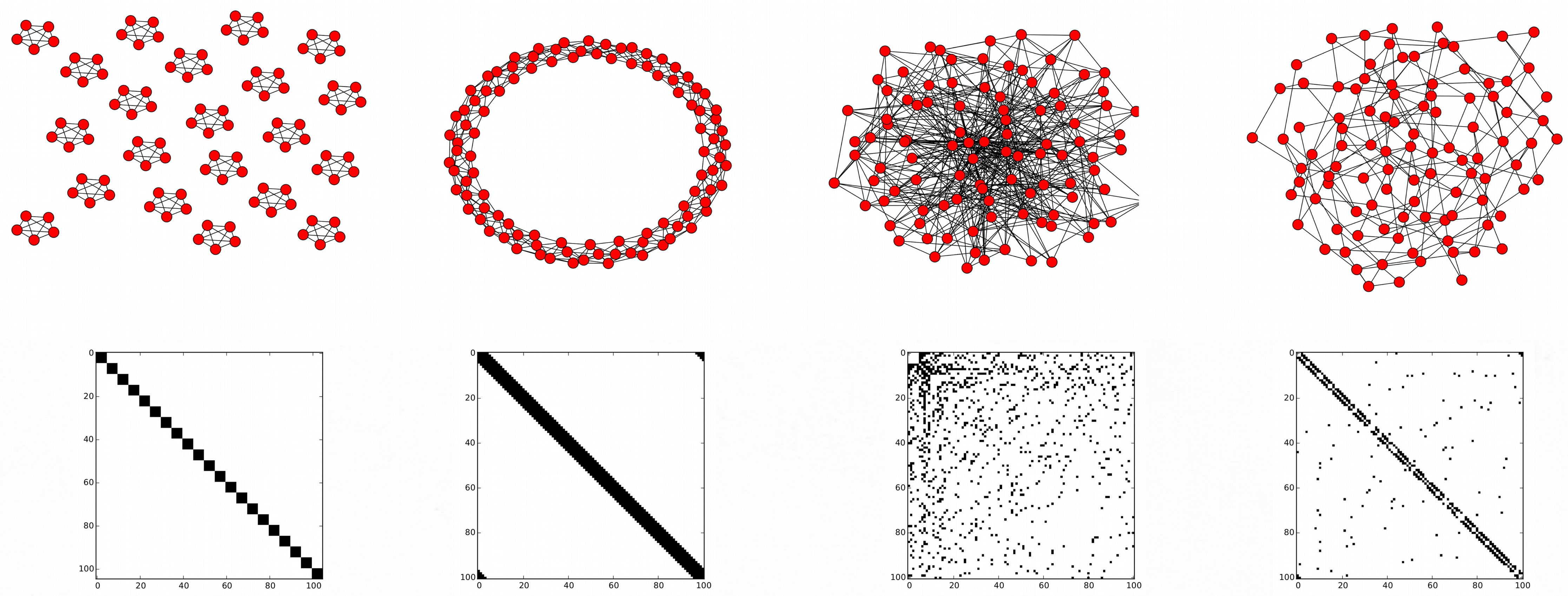


Figure 3: Different network structures used, in order: Fixed patch vicnity, Sliding window vicinity, Scale-free network, Small world network plotted as graphs and adjacency matrix

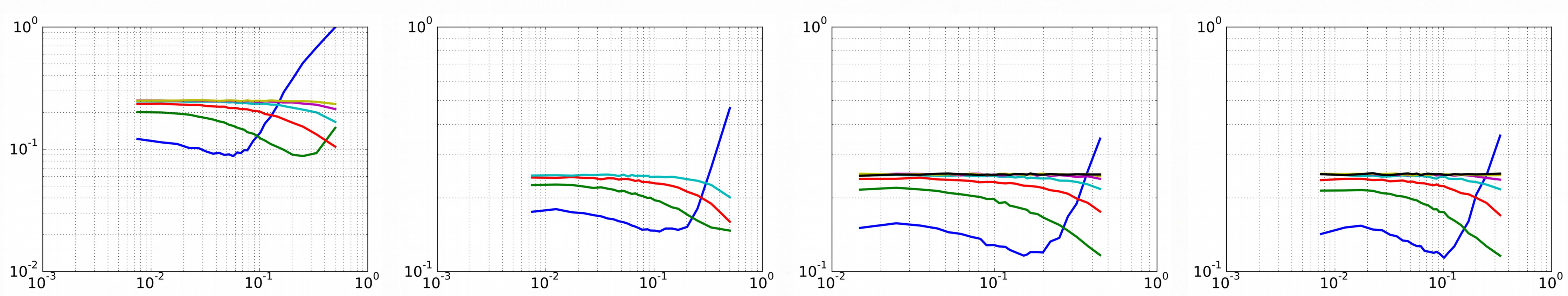
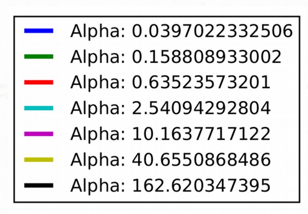


Figure 4: Normalized variance for different network structures, in order: Fixed patch vicnity, Sliding window vicinity, Scale-free network, Small world network. Different colors represent different values of control parameter α



From results of different network topologies it can be seen that the best performing ones have isolated communities, ie. fixed patch wins versus sliding window. This is true for values of α smaller than its optimal value, while the communities become irrelevant when optimal α is exceeded.

For each value of α a different value of β (optimal number of communities) is found. This means that for different conditions of the system, defined by the number of agents and their cognitive abilities, we can find an optimal number of communities that the system should be divided into.

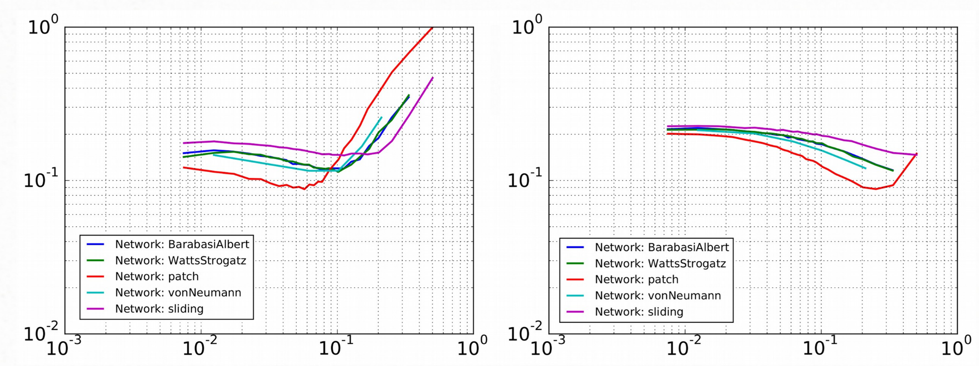
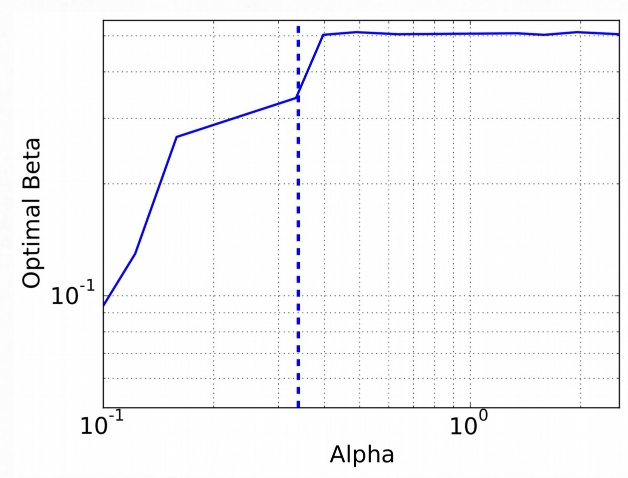


Figure 5: Confrontation of different topologies for the same controll parameter value

Conclusions

Our first and rather simple result is that to raise the efficiency of resource distribution we have to bring the system as closely as possible to the optimal value of its control parameter α. This approach is to be preferred whenever possible, while including the vicinity information in the model can make for a more efficient resource distribution when optimal α can not be achieved.

The experimental results have led us to the conclusion that fixed and isolated communities are to be preferred when possible, while we have proposed a different approach when simple patch vicinities are not an option. The definition of a hierarchical community is a hybrid approach based on the preferential attachment rule as used by scale-free networks and two properties of small world networks: small average path length and high clustering. We propose an algorithm that divides the entire set of agents in a number of communities estimated to be optimal for a given value of α, constructing each community as a scale-free network and then use the rewiring mechanism of small world networks between these scale-free communities.



Data: Number of Agents N, Brain size M
Result: Hierarchical network structure G, CG
$\alpha \leftarrow \frac{2^M}{N}$;
$\beta \leftarrow$optimalBeta(β);
for $i \in [1, \frac{N}{N\beta}]$ **do**
  $C_i \leftarrow$generateBarabasiAlbertGraph($N * \beta, 0.5 * N * \beta$);
  for $j \in E(C_i)$ **do**
    Rewire j with $P = 0.05$;
  end
  $CG_i \leftarrow$generateCommunityGame(C_i);
end
$G \leftarrow$generateGlobalGame();

Figure 6: Optimal β graph and the proposed algorithm to use a hierarchical structure

Literature cited

[1] Damien Challet and Y-C Zhang. Emergence of cooperation and organization in an evolutionary game. *Physica A: Statistical Mechanics and its Applications, 246(3):407-418, 1997.*
[2] W Brian Arthur.Inductive reasoning and bounded rationality. *The American economic review, pages 406-411, 1994.*

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