SIMULATIONS OF OLIGOPOLISTIC MARKETS WITH ARTIFICIAL AGENTS: DECISION PROCEDURES AS EMERGENT PROPERTIES OF ADAPTIVE LEARNING

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ABSTRACT

While economic models of strategic interaction among autonomous decision-makers are usually based upon principles of optimisation, this work focuses on "satisfying" decision procedures. A flexible simulator of oligopolistic economic environment, where autonomous decision-makers evolve their decision procedures using a learning and adaptation process, has been built. Each artificial agent is implemented using a feedforward neural network. The unsupervised learning of the agent is obtained using genetic algorithms which evolve the structure and weights of the neural network during simulations. The obtained results show that as the complexity of the environment overwhelms the cognitive abilities of the agents, decision procedures emerge that are at the same time simple robust and "satisfying".

1. ECONOMIC FRAMEWORK OF THE SIMULATION: BOUNDED RATIONALITY THEORY AND RULE-BASED BEHAVIOURS

The main purpose of this study has been to develop suitable modelling techniques for a "satisfying" approach to the strategic environment of oligopolistic markets.

Usually the framework of the researches of such economic environments, is made up by the game theory and the general equilibrium theory. Both theories deal with the problem of the final state of the system and the existence of equilibria. The processes which lead to equilibria and in general the dynamic aspects of the system are not analysed in deep.

Further limits of this theoretic framework can be examined with regard to the hypothesis assumed upon the decision makers, actors of the strategic interactions (see Hodgson (1988)).

Probably the hard-core hypothesis of the rational theory is represented by the maximisation one. It states that the economic agents operate consciously by basing on some environment variables to maximise a goal variable like the expected utility. Models based upon this assumption can hardly account for some behaviours of agents observed in real economic interaction systems, that we reproduced with our simulations. Bounded rationality theory introduced by Simon, which states that the agents have goals expressed in terms of a minimum to reach offers a better framework to account for the observations (Newell and Simon (1972)).

Another hypothesis that rational theory usually assumes is that the information available to the agents is complete. Each agent knows his own decision alternatives and preferences, the ones of the opponents and their being rational, the payout matrix, the environment and so on. In our simulations agents have limited information about the environment and do not know the strategies of the rivals, thus they have to create a representation of them by observing their reactions to their actions.

Another hypothesis usually assumed is that of the unlimited cognitive abilities of the agents. Each agent is able to get the best from the information obtained from the environment, having unlimited computation capacities. In our simulations we implement agents that have limited computation capacity. In fact our aim, in the positive theories spirit, is to make models which have a “weak isomorphism” with real economic systems, so that the evolution of simulated systems is for some aspect similar to the real ones (Dosi (1994)).

To conclude this theoretic justification of our simulation we observe that assuming the strong hypothesis said, even in the weaker form of the “as if” of Friedman (Friedman (1953)), means to have incomplete theoretic instruments to account for some economic behaviour. For these reasons we believe that using the bounded rationality theory along with the rational decision theory to explain and to model situations that not fit the last one. In this sense one of the aims of our work has been to show that when the complexity of the environment reaches a level too high for the agents limited cognitive capacities, agents can’t behave rationally but have to adopt some decision procedure simple enough to compute and robust enough to lead to a satisfying level of outcome in several different environmental situations.

The basic idea that lies behind our artificial agents (Nelson and Winter (1982) and Holland et al. (1986)) is that economic agents face decision problems not by maximising a sort of function, but by adopting rules of action that have shown to provide a good outcome in the past experience. In particular a rule is a procedure that links a precise action to a particular state of the world, or, better, to the agent’s representation of it. When the agent gets some information about the environment, he creates a representation of it and reacts by choosing the use of the procedure that was most profitable in similar situations.

While acting in the environment, the agent undergoes a learning process. He has other procedures along with the one that he uses, we can call them “different hypothesis on the world”, that he tests during the action. If the agent realizes that one of this hypothesis would have provided a better outcome if used instead of the procedure effectively applied, this becomes the procedure that he will use the next time. New rules are generated by mixing the best old rules, when for a while no one of the “hypothesis on the world” succeed to substitute the rule applied. This kind of learning is a typically evolutionary one. The mechanism that leads the agent to learn how to face the environment by developing good procedures is in essence a genetic algorithm (Holland (1975)).

2. ARTIFICIAL INTELLIGENCE TOOLS USED FOR THE SIMULATOR

At this point we analyse how we simulated an agent using some artificial intelligence tools. The model of agent we will explain can be used in any simulated decision context where the agent’s learning process can be realised with several proofs and errors, and the success can be quantified each time. In the next paragraph we will introduce the particular environment where we have used our agents, the monopolistic and oligopolistic markets. Our efforts have concentrated on solving the well known problem of simulations in positive economics: to create decision makers that learn through unsupervised processes, and that do this while acting in the environment. These are the necessary conditions to create simulated systems that have at least a “weak isomorphism” with the real systems. After reaching this minimum condition we can hope that the behaviours of the artificial agent and systems created are similar for some aspects to the real ones.

Each rule of one agent is implemented by a classic feedforward neural network made of three layers: input layer, hidden layer, output layer. The net gets standardized between -1 and +1 quantitative information from the environment through the input layer, then it makes an internal representation of environment using the hidden neurons states, and finally it decides a particular action by activating the output neurons. Hidden and Output units have sigmoidal transfer functions, and the input units are simply signal repeaters (Pessa (1993) and Pessa Penna (1994)).

Each rule/network is coded by a matrix using the following criterion:

	I 1	I 2	I 3	I 4	I 5	O 1	O 2	O 3
1° hidden	95	470	937	-439	26	996	-625	65
2° hidden	-735	380	385	698	-889	-362	452	-597

Each line is made by the weights connected with one particular hidden unit. The first group of weights of a line connects the input units to the hidden unit, the last group weights connects the hidden unit to the output units.

At the beginning of the simulation the rules of each agent (weights of the nets) are randomly generated. Then every rule is tested with the environment to get a number that synthesizes its fitness. This is done by sending the inputs to the net, by getting its output(s) and by getting the answer of the environment. The number that synthesise the fitness of the test is cumulated over time as tests follow, thus cumulated fitness is gained for each rule. On every period/test each agent uses the rule that has gained the highest cumulated fitness until then. The opponent have to use their best rules and test their hypothesis on the world, against that rule. The fitness is multiplied by a coefficient (around 0.98) that is the inverse of the number of existing connections. This has been done to make the nets prune “parasite connections” that would make their interpretations difficult.

After a certain testing time during which a precise rule has the highest cumulated fitness and therefore is used, the agent substitutes his hypotheses on the world because they have shown not to be competitive with the rule applied. This is done through a genetic algorithm mechanism.

Each rule has a “DNA” made by the sequence of the net weights (the sequence of the matrix lines shown before). The new rules are generated from the old best ones in two ways. The first way consists in taking one old rule and applying some mutations. The second consists in taking two old rules, generating two new rules by mixing the old by crossing-over, and applying some mutations. The crossing-over never splits any group of weights corresponding to one hidden unit (one matrix line). This ensures that the rules are mixed by taking the whole subnets corresponding to one single hidden unit, this facilitating the finding of complex high performance schemata (Holland (1975)).

Mutations are of two types. The first type randomly creates or destroys connections between units, the second makes little variations on some randomly chosen existing connections. In other words the first kind of mutation changes the structure of the net, the second one reproduces the fine tuning of weights usually obtained in the nets learning process through algorithms like back-propagation (in our case the process used is a random walk).

In the first simulations every agent had the goal of increasing the profit. This was made by selecting the networks according to the profit produced. The system we obtained was very unstable: one agent became soon monopolist by fixing price under the ones of others, even if the selection of networks was done over several periods (long run profit). For this reason we have introduced a mechanism of multiple goals based on a threshold principle (Simon (1974)). A threshold is fixed for each goal. In each period in which the reproduction of networks is done, the effective value of each goal is compared with the threshold and the difference, after being divided by a dimension index, is transformed using a sigmoidal function for a further standardization. The goal with the lower standardized value is the goal used by the agent in the following interactions.

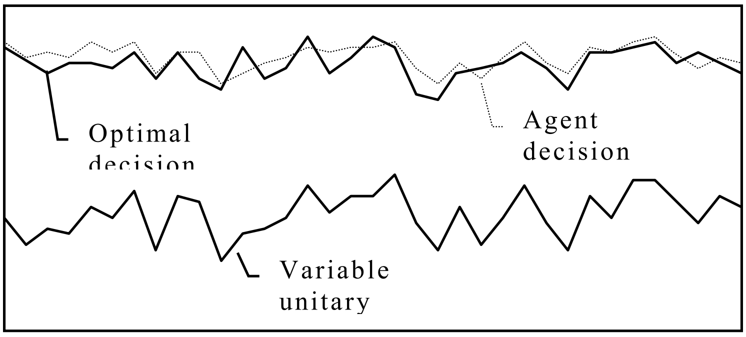
The simulator allows to change several parameters like the following ones: the number of hidden units of nets, the member of tests after which hypothesis are changed if always the same rule is used, the number of agents, the number of rules generated from one old rule and by crossing-over, the different mutations probabilities and entities, the parameters of multiple goals mechanism, the economic parameters as the level and elasticity of demand, the elasticity of market, the fixed and the variable costs.

3. SIMULATIONS OF OLIGOPOLISTIC MARKETS

In order to test the capabilities of our model, we started to simulate a monopolistic market. The economic environment considered was the classic one, except that the monopolist did not know the curve of demand. The intercept of demand and the variable unitary cost (constant) had a random variation of +-20% and +-30% respectively at each time. The variables known by the agent were: the fixed cost (CF), the variable unitary cost of present (CV) and past period (CV-1), the quantity produced (Q-1) and the price fixed (P-1) in the precedent period, the variation of profit in the last two periods (dPro). The decision variable was the price (P). The results have been the following ones. Given the economic parameters, the structure of the nets tends to converge to a precise one, for example the next one (the blanks are missing connections):

	CF	CV	CV-1	Q-1	P-1	dPro	P
1°hidd.		+630					+403
2°hidd.			+383				+257
3°hidd.							
4°hidd.							

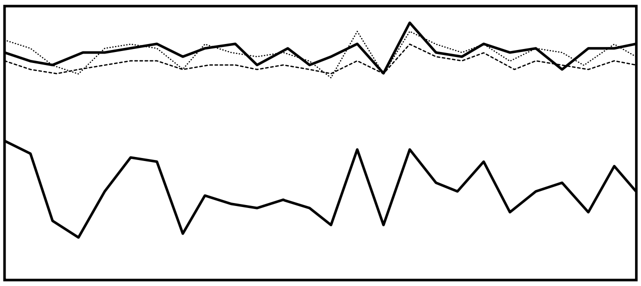
This simple structure is enough to yield a very good performance (demand is unknown):

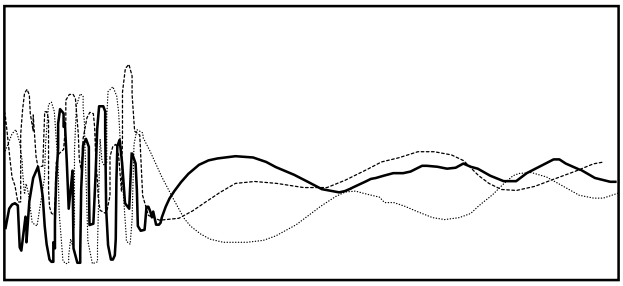


What is important is that our agent tends to show the ability to “understand” that the informations relevant for him are the ones about the costs, and that the other informations about the past are not important. This behaviour can be inferred by looking at the net structure shown before, namely to which columns the existing connections correspond. Another interesting result is that the agent reaches a good performance using a little amount of its cognitive potential. A further theoretically important consideration is that the agent fixes the price with the rule of mark-up given that the demand is unknown for him.

We consider now the oligopolistic markets. We suppose a linear global market demand, unknown for the agents, which varies randomly at every period. Every agent has a certain amount of fixed costs and unitary costs which are constant for each production unit but randomly variable in every period. Every agent has to fix the price in each period. Then the market price is calculated on the base of the old market shares and the present agents' market shares are changed proportionally to the ratio between the average market price and the fixed price.

The information given to every agent are the ones seen for monopolist plus the following: prices of each agent (Px-1), average market price (PM-1), aggregate demanded quantity (QM-1), own market share (S-1) and its variation (dS). The following graphs show the results of a 2000 interactions simulation with three agents. The first one shows the variable unitary cost (equal for every agent) and the prices fixed by the three agents in the last interactions: the mark-up rule has emerged as a profitable and robust rule. The second graph shows the market shares during the whole simulation: the multiple-goal mechanism makes the system stable enough. The nets structure mutations were stopped after 400 interactions to obtain a more gradual learning rate after an initial phase of environment exploration.





The results are also confirmed by the structures of networks emerged during the simulation. The following table shows for example the structure of the last rule used by the third agent:

	CF	CV	CV-1	P1-1	P2-1	PM-1	QM-1	P-1	S-1	dS	dPro	P
1° hidden								-500	+453			+589
2° hidden		+472		-103				+74		-727	+690	+327
3° hidden		+77	-298					+446				

The results so far obtained confirm the theory stated at the beginning: the more the environment is complex, the more the agents tend to concentrate on important information. Moreover the experience we have had suggests that the researches carried on by the neuronal nets theory provide very interesting instruments to build economic models concerning with the decision theory, since they allow to study (within the limit of realism of models) in experimentally controlled situations the relationships between the system and the psychological aspects of agents.

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