“BEYOND EXPERIMENTAL ECONOMICS. TRADING INSTITUTIONS AND MULTIAGENT SYSTEMS”

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ABSTRACT

The ancillary hypothesis of unbounded rationality has dominated economic modelling for several decades. This extreme assumption has been relaxed in a fast growing literature under different headings: new institutional economics, experimental economics (E.E.) or behavioral and evolutionary economics, to name a few. On the other hand, agent-based modelling is an active area of research with successful applications in Engineering and Science. In this paper we discuss the application of MultiAgent Systems (M.A.S.) to handle the social dimension of economics and design an appropriate artificial agent wich is “resource-bounded-rational”. We simulate alternative market trading institutions which have been extensively studied in E.E.. We demonstrate the possiblities of an artificial agent to accommodate alternative market institutions, thus extending the scope and use of E.E. which so far needs real agents.

KEYWORDS. Trading Institutions. Experimental Economics. Multiagent Systems. Bounded Rationality.

INTRODUCTION

The ideal of rational decision making requires agents to maximize some measure of expected utility that reflects a complete and consistent preference order and probability assignment over all possible contingencies plus enough time to solve the corresponding maximization problem. This requirement appears too strong for a realistic description of individual agents behaviour that are studied in economics. Most approaches within the orthodox economic tradition have avoided the central issue of limited cognitive capabilities, by introducing transaction cost and imperfect information hypothesis, *institutionalists* or learning heuristics, norms, and other imports from sister disciplines: *evolutionary economics.*

The overwhelming evidence, such as that provided by Tversky and Khaneman (1981), indicates that people are capable of a wide variety of substantial and systematic reasoning errors relevant to economic decisions. Those errors are related to economic conditions such as deliberation cost, incentives and experience learning.

For these reasons a growing a meaningful literature has developed under the name of experimental economics, trying to grasp the actual functioning of trading institutions and economic organizations. Once these contributions have been credited as real economics, a further step could perhaps be taken: why no substitute real agents for artificial ones when conducting experiments in economics?

Artificial intelligent agents are used in Artificial Intelligence (AI) with appropriate protocols and languages. So it was just natural to search in the AI literature for a suitable one to represent the bounded rational nature of human cognition and economic choice. Many of the defined agents we could find in AI were not capable to account for the dimensions of a bounded rational agent. And this was a necessary step for a succesful application of AI to socially focused economic modelling. We explain in the following lines our initial experience in this search.

We illustrate our artificial experiment with the simplest of the possible trading institutions, that however proved to be quite complex: a posted offer auction, under uninformed and informed buyers. The results show the importance of the trading protocoles, and overall the long way ahead to understand other more complex market institutions. A corner stone facet of the wider field of organization economics as advocated by Herbert Simon (1991).

BOUNDED RATIONALITY AND EXPERIMENTAL ECONOMICS

In conventional neoclassical economics (n-c) agents behaviour follows the result of a constrained maximization problem. The choices are made: (1) among a given fixed set of alternatives; (2) with known probability distributions of outcomes for each; (3) in such a way as to maximize some expected utility-cost functional. These are convenient assumptions, setting the foundations of an elegant body of theory, compatible with econometric testing in an aggregate setting. Thus we could talk of the representative agent. Even more, to reach a consistent equilibrium states, they underline the role of the representative agent by assuming that agents know the correct model.

No wonder people outside the academic world find this approach bizarre. And as Knight (1921) put it, they prefere to be irrational and work with simpler rules. “It is evident that the rational thing to do is to be irrational, where deliberation and estimation cost more than they are worth”. Thus a reinterpretation of n-c economics came up in the form of a “yes, but as if” argument. No one would state that people are unboundedly rational, only that they act as if they were unboundedly rational. If models from rational agents are not falsified by observed aggregate data, they are accepted as positive economics.

Since there is overwhelming evidence of bounded rationality, from psychologists, sociologists and experimental economics, a second more subtle line of defence is proposed. We still can gain insight into economic relationships under the n-c assumption by allowing explicit violations of unbounded rationality, as far as they could be translated into some kind of measurable costs: deliberating, transaction, agency or risk premium costs. We think that this extension of n-c is a useful one, that can be both challenged and reinforced by a full behavioural approach. This logic cuts both ways. This is the ultimate motivation of our research. And that is why we will use the term resource-bounded-rationality since in the final interpretation of the behavioural model outcome it wíll be useful to recast it as far as possible in the n-c-shell.

The term bounded rationality is used to designate consistent choice that takes into account the cognitive limitations of the decision maker (limitations of knowledge, partial knowledge of other agents decisions and computational capacity) and the institutional veil. Thus instead of assuming a fíxed set of alternatives among which to choose, we may postulase a process for generating alternatives. Instead of assuming known lotteries for the outcomes, we may propose alternatives for dealing with uncertainty that do not assume knowledge of probabilities. Maximization of a utility function will be replaced by a satisficing strategy.

Take the following classroom example, Pindyck et al. (1995). Three contestants A. B and C, each have a balloon and a pistol. From fixed positions, they fire at each others balloon. When a balloon is hit, its owner is out. When only a balloon remains, his owner is the winner and receives a $1000 prize. At the outset, the players decide by lot the order in which they will fire, and each player can choose any remaining balloon as his target. Everyone knows that A is the best shot and always hits the target; that B hits the target with probability 0.9 and C with probability 0.8. Which contestant has the highest probability of winning the $1000? When asked to advance an answer within five minutes, some will come up with a reasonable and correct one: Contestant C.

The intuitive argument -cognitive efficient- is that, as in real life, under perfect rationality , the observad fact is that mediocres are the winners as well. Of course, in this case, procedural learning will lead to the same answer that substantive one.

Even more; we use as well as in n-c, ancillary assumptions about the emotional attitudes of the contestants: aggressive selfishness. And a well specified protocol for the game, a sequentially random order.

Modelling bounded rationality (the tools for) and models of bounded rationality (substantial conclusions derived from models) have been the purposes of the growing literature in experimental economics (e-e). There has been serious concern on the question of wheter e-e should be regarded as an econometric tool. We mantain that if it is true that theory needs measurement (Marshack, 1948), it is no less certain that measurement needs theory (Frisch, 1933). This is in fact the virtuous circle of the scientific progress of a discipline. Economics is no exception. E-e is used to derive quantitative implications of economic theories, and to test the realism of auxiliary hypothesis.

Within the narrower field of trading institutions, e-e has revealed the importance of protocoles, and how contracts are confirmed; who makes price proposals, information biases and the lot. And last but no less important, laboratory experiments are a data source which may be complementary to happenstance data or much cheaper to obtain in social cost terms. Is it not interesting to see to what extent the evidence gathered from experimental auctions could be reproduced in artificial settings? This is the central aim of the paper.

ARTIFICIAL AGENTS TO DEAL WITH BOUNDED RATIONALITY.

To see whether MAS as developed in AI can be of some help in economic modelling let us to describe the social facets of an economic agent. What we do in general will depend upon other agent choices.And because of this a new dimension has to be considered in designing an economic agent: emotions and motivations. This is in itself a formidable task, very much neglected even by psychologists more concerned with cognition than with emotion, see Elster (1998). Thus the economic activity of our bounded rational agent is a social relationship.

Even more. The economic activity takes place in a particular setting. Thus, the institutional veil is an essential item in good economic modelling. Think about the market and price discrimination. Price will be determined not only by the supply and the demand, but by the way the trade is organized. Auction protocols are essential in price determination.

For these two reasons our agent moves into a two dimensional grid: degree of rationality and degree of opportunism as a drastic and synthetic indicator of emotions. And within this grid, under the institutional protocols, our agent will be moving in alternative scenarios. Team theory or altruism economics, general equilibrium, temporal equilibrium, transaction costs and agency theory, or governance structures.

On account of our arguments above, and within a MAS setting, we endorse our resource bounded economic agent with the following features:

- Uncertainty: imperfect information about the environment and the institutions.

- Limited cognitive capacity: she cannot evaluate all the alternatives within the sample space. As a result she cannot forecast the possible results of her decisions.

- Time: an agent acting in a time-critical domain must decide what to reason about, when, and for how long. Too little reasoning can lead to mistakes, while too much can lead to lost opportunities, and deliberation costs.

- Finite length memory: we have to specify a forgetting factor for agents, as information processors.

- Learning. Agents learn in both modes: procedural and substantive learning.

- Communication channels and protocols that the institutional setting offers to agents.

- Agent social behaviour. The respective advantage of different interaction attitudes of simple agents in a common simulated environment: solitary, parasite, selfish and help-giving.

In parallel but without mutual crossbreed, AI has been developing an artificial intelligent agent. There is not a proper and widely accepted definition of intelligence in the field, but according to Gasser (1991) to qualify a machine as intelligent it should have autonomous social capabilities. It is based on the socio-biological theory that primate intelligence first evolved because of the need to deal with social interactions. That in turn means that any contribution towards the construction of artificial intelligence agents, perhaps from behavioural approaches ar ours, will fruitfully feed other disciplines.

Nevertheless three key issues on intelligent agents should be considered: agent theory, agent architecture and agent language. In López (1998) and López et al. (1998) we discuss about those. Our personal choice is the CPM Agent as understood by Edmonds and Moss (1998); and the classical approach to build bounded agents is to view them as a particular type of knowledge-based system (KBS).

A PREMIER: A POSTED OFFER AUCTION

Our approach to build agent based models in trading institutions follows Vidal and Durfee (1996). We think useful to increase the agent complexity: a) agents ignore other actions; b) agents have simple models about other agents behaviour; c) agents have complete models about other agents behaviour. We use SDML to program and simulate our model (see Moss et al. 1998).

The cognitive architecture ACT-R of Anderson (1993) is the underlying architecture used to develop our agents. This theory is one empirically sounded and well validated by experimental data with humans.

The markets that we model are organized through the posted offer auction institution. Perhaps one could think in the market for air tickets, package holidays, hotel booking, etc. We try two experiments. The first one (market 1) assumes no knowledge from the buyers. In the second one (market 2) reputation, or prior information about the sellers is allowed to the buyers: the bigger seller companies, the cheapest, the more likely to accept the buyers initial offer.

Although a posted offer is about the simplest form of auction, there are many vatiations and special cases. The set of buyers (bids) is large and so is the set of sellers (asks). We assume for each seller ***s*** third degree price discrimination: p_1^s, p_2^s, p_3^s. The quantities offered are limited by production capacity Q, that the sellers assign: $q_1^s + q_2^s + q_3^s = Q$, respectively to the different prices. The actual sellers income comes from a "mark-up" policy. That means that they know the marginal cost and fixed costs, around a mean return value for the sector.

The buyers have their reserve prices and preferences on the "quality" of the product offered through the third degree discrimination policy of the sellers. They will not communicate to the sellers their reserve price. The time for each round is limited. Thus the buyers will have to decide if they buy or not according to their preferences in terms of price and quality.

The auction protocole is as shown in figure 1. At time 1 the buyer requests bids for some sellers. At time 2 the sellers send their prices for that good. At time 3 the buyer picks one of the bids (or not). At time 4 the commitment is sent to the selected seller. At time 5 the seller will confirm or not the purchase and send the good.

In the second version of the experiment the buyers are allowed to have prior beliefs about the sellers attributes, reliability, production capacity, etc.

We provide the buyers with a vector strategy with components such as: time spent in searching, price-quality relationship, and failure to get the product. In this way we endorse the buyers with elemental “emotions”. Figure 2 shows the rules to formulate the buyers strategies under SDML.

MAIN RESULTS AND CONCLUSIONS

Selected results which so far we have to take as provisional ones, are reported in figures 3 and 4. There are 10 trading cycles per round and the market was simulated with 30 rounds or sessions. The number of sellers is 15 and the number of buyers is 300.

For market 1 all prices in the third class (cheap) and most prices for the second class are matched prices. There is no regularity in prices and all the sellers, even the least efficient, are able to sell, although fewer quantities. The length of the price set has a range of 16 to 25. The average trade volume of trade is more uniform all along the last five days .

For market 2 the number of transactions per round (along the five days) is greater than for market 1; thus reputation helps to increase market volume. Daily average transactions tend to concentrate at the beginning of the five days period, and just not to be left out, an increase is observed in the last day. The least efficient sellers will have no transactions at all and in this simple model they will be out of the market. The length of the realized prices is shorter than for market1.

Surely these results are self evident and too simple. But this was the initial aim of the paper. Just to show that our artificial intelligent agent are capable to reproduce expected behaviour in a robust simple case.

There are extensions on the way, to test the available literature in experimental economics within the many variations of the posted offer auction.

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FIGURES

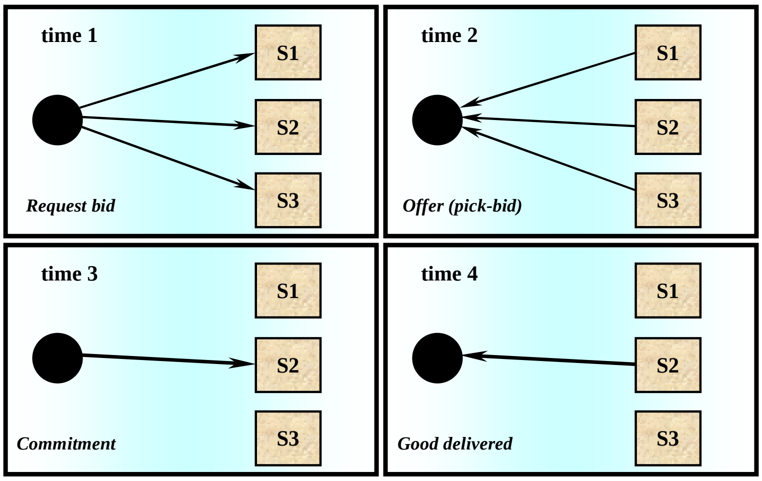

Figure 1: Trading Protocole

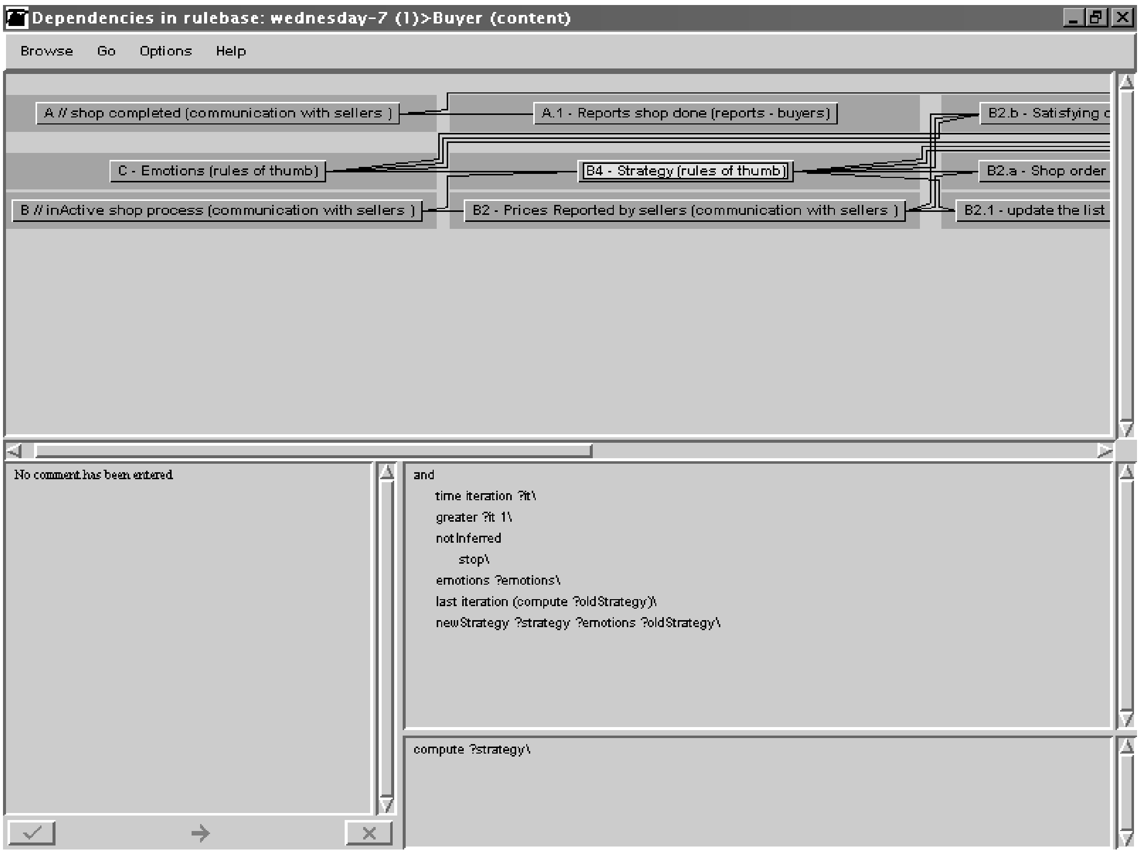

Figure 2: View of the buyer’s rules hierarchy and the Strategy rule.

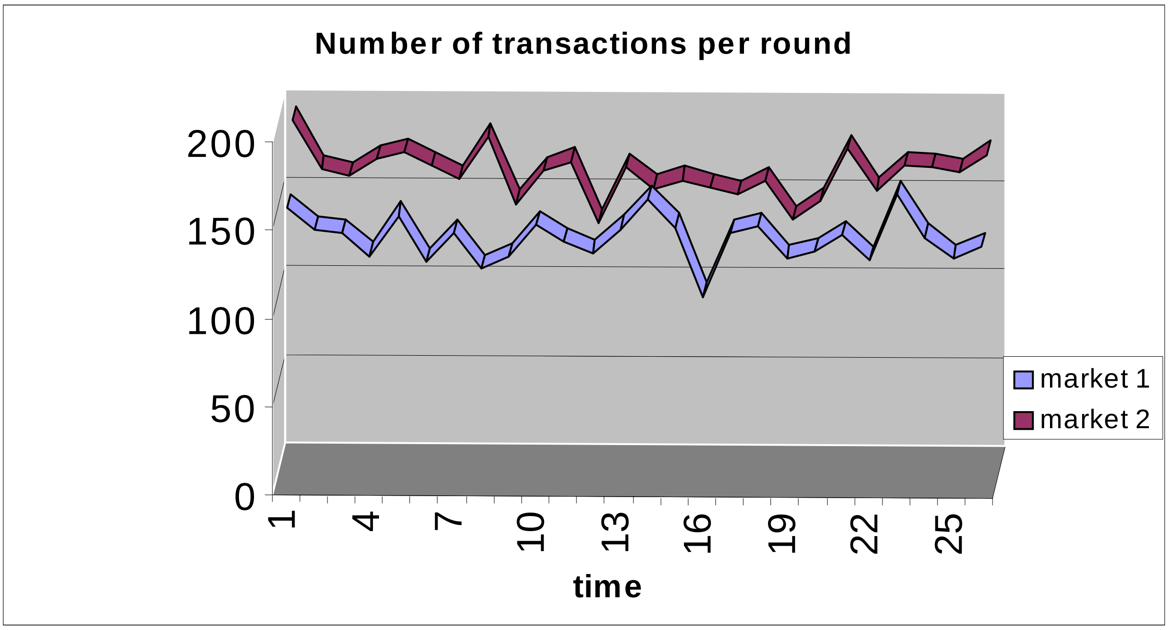

Figure 3: **Number of transactions per round.**

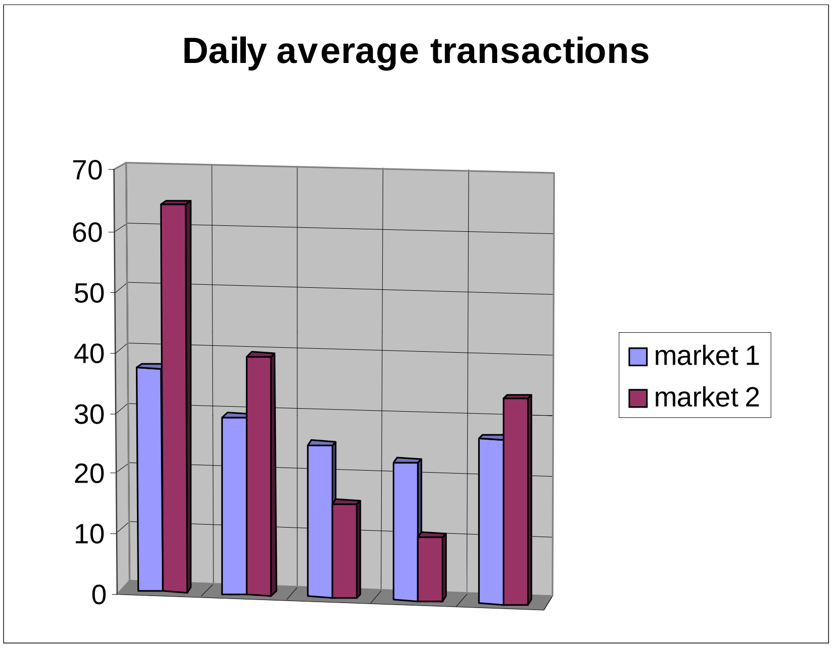

Figure 4: **Daily average transactions**