THE SOCIAL DIMENSION OF ECONOMICS AND MULTIAGENT SYSTEMS

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ABSTRACT

The ancillary hypothesis of unbounded rationality has dominated economic modelling for several decades. This extreme assumption about the behaviour of economic agents is relaxing recently in a fast growing literature under different headings: new institutional economics, experimental economics, agency theory, transaction costs, or behavioural 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 MAS to accommodate the social dimension of economics and describe an appropriate artificial agent which is "resource-bounded-rational". We show how to design an agent and the corresponding architecture, which under the SDML of Moss et al. (1998) is a valid representation of economic cognition and behaviour.

KEYWORDS: Bounded Rationality, MultiAgent Systems

Herbert Simon, introduced and developed since then, the concept of **bounded rationality** more than thirty years ago. He proposed to replace the idea of utility maximization by a more realistic view of economic behaviour involving satisfying and the adaptation of aspiration levels to success and failure. To accept that the economic agent learns in two modes, *Substantive* (the result of normative maximizing models) and *procedural* (people behave coherently by following reasonable procedures but sometimes making suboptimal decisions as a result). He pointed out that in view of the enormous complexity of the decision tasks facing consumers and firms, optimization transcends human **cognitive** capabilities. Some people are well convinced as ourselves, by Simon´s arguments.

Artificial intelligent agents are used in the field (AI) with appropriate protocols and languages. So it was just natural to search in the AI literature for a suitable intelligent agent 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 accommodate the dimensions of a bounded rational agent. And this was a necessary step for a successful application of AI to -socially focused- economic modelling. I explain in the following lines my incomplete experience in this search. What do we understand by bounded rationality? Why bounded rationality in the first place? Can we define an artificially intelligent agent to match the dimensions of the economic agent with resource bounded rationality? I hope you will agree with me that the answer is a reasonable YES.

ECONOMICS AS A SOCIAL SCIENCE AND RESOURCE BOUNDED RATIONALITY.

In conventional neo-classical economics 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 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 prefer 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 will 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 fixed set of alternatives among which to choose, we may postulate 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 other's balloon. When a balloon is hit, its owner is out. When only a balloon remains, its 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 observed 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.

To conclude, bounded rational agents will be used because, as Conlisk (1996) states, there is abundant empirical evidence that it is important. Models of bounded rationality have proved themselves in a wide range of impressive work. The standard justifications for assuming unbounded rationality are unconvincing and their logic cuts both ways. Deliberation about an economic decision is a costly activity, and good economics requires that we entertain all costs. And overall because it is simply a fascinating thing to do.

AN INTELLIGENT AGENT FOR SOCIALLY FOCUSED ECONOMIC MODELLING.

In the last paragraph we have shown why bounded rationality should be incorporated in the individual behaviour in economics. Some additional comments are in order to see whether M.A.S., as developed in A.I. can be of some help in economic modelling with a social focus.

What I 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 any good economic model. Think about the market and price determination. 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: He cannot evaluate all the alternatives within the sample space. As a result he cannot forecast the possible results of his 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.

— Agents Social behaviour. The respective advantage of different interaction attitudes of simple agents in a common simulated environment: solitary, parasite, selfish and social. These have been defined along the two dimensions of self-sufficiency and help-giving .

The following references contain additional comments about these features. Parkes (1997), Vidal and Durfee (1996), Moss and Sent (1998), Edmonds (1998), Russell (1995), Russell and Wefald (1991), Zilberstein (1998).

A PROPOSAL FOR A SOCIALLY INTELLIGENT AGENT

In parallel but without mutual crossbreed, Artificial Intelligence 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 capacities. 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 intelligent agents, perhaps from behavioural approaches as ours, will fruitfully feed other disciplines.

As pointed out by Wooldridge & Jennings (1995), three key issues on artificial intelligent agents' should be considered:

❍ Agent Theory; it is essentially the specifications from theorists: the conceptualisation, the properties and the knowledge representation and reasoning.

❍ Agent Architecture, that is the way from specification to implementation. In particular we have to specify the learning algorithms and the way time is introduced.

❍ Agent Languages, the software especially concerned with agent modelling facilities, such as original and users`s primitives, rulebases, etc.

Agent Theory

There are some definitions in the literature for the term agent. Several authors have shown a taxonomy based in the name of the researcher who proposed it and the term agent (*MuBot Agent, Hayes-Roth Agent, Maes Agent, etc.*). In an extended report, López-Paredes (1998), several approaches to agent theory in the AI literature are analysed. They probably could be adapted and extended to cover the futures of a resource bounded economic agent. Our personal choice is the 'CPM Agent' developed by Moss, Edmonds and Wallis.

As Edmonds (1998) states this agent does not have perfect information about their environment. In general they will only acquire information through interaction with the dynamically changing environment.

They do not have a perfect model of their environment and exhibit limited computational power, so they can't work out all the logical consequences of their knowledge. They also have other resource limitations (e.g. memory). The mechanisms of learning dominate the mechanisms of deduction in determining their action. They tend to learn in an incremental, path dependant way rather than attempting a global search for the best possible model. Even though they can't perform inconsistent actions, they often entertain mutually inconsistent models, a feature at odds with neoclassical economics.

Finally, bounded rationality necessarily requires optimal meta reasoning, that is reasoning about reasoning. We need a model of rationality that judges agents not only by their actions in the world, but also by the reasoning process by which they choose those.

The agents´ model and his core characteristics are as shown in fig. 1 and fig. 2.

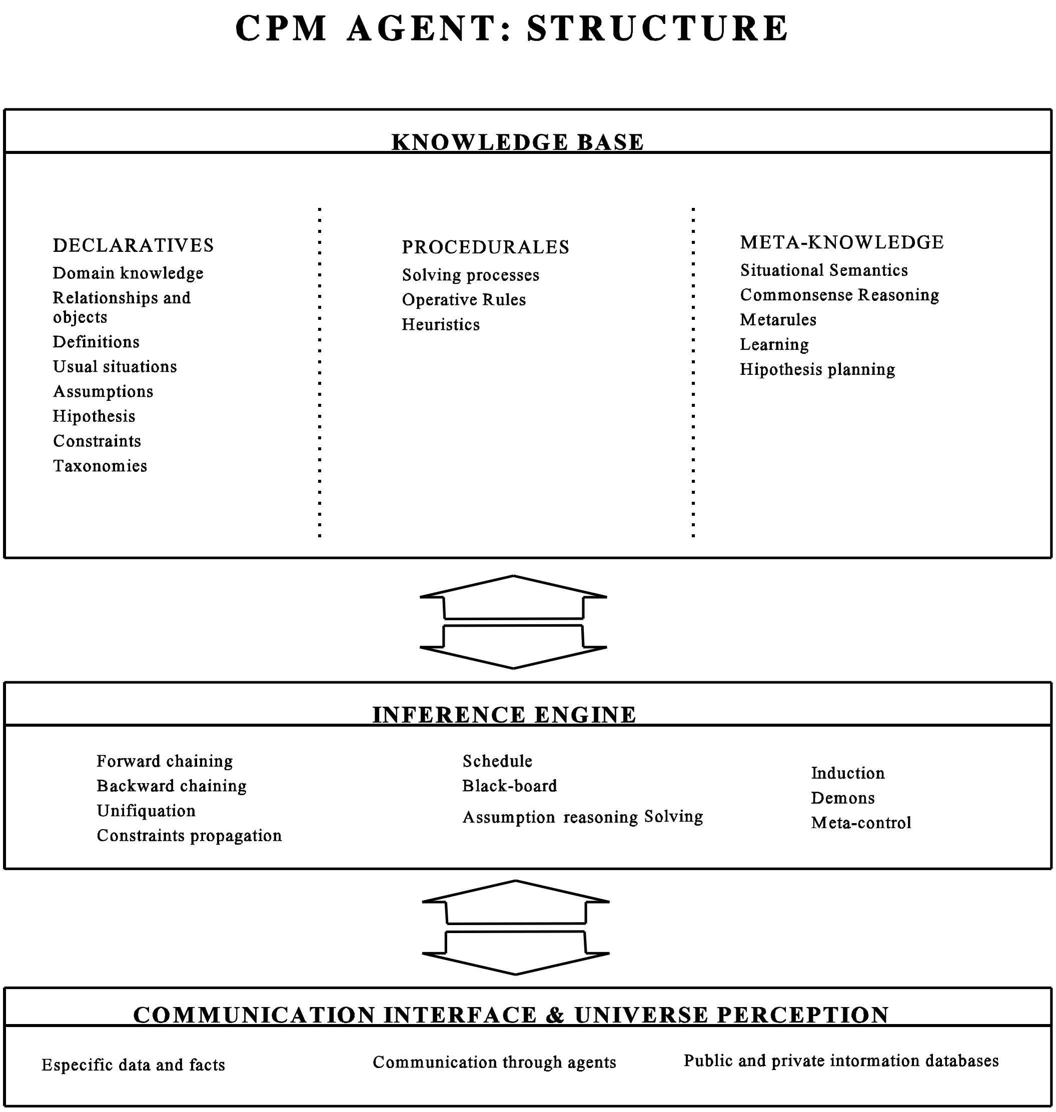

Figure 1: CPM Agent internal structure

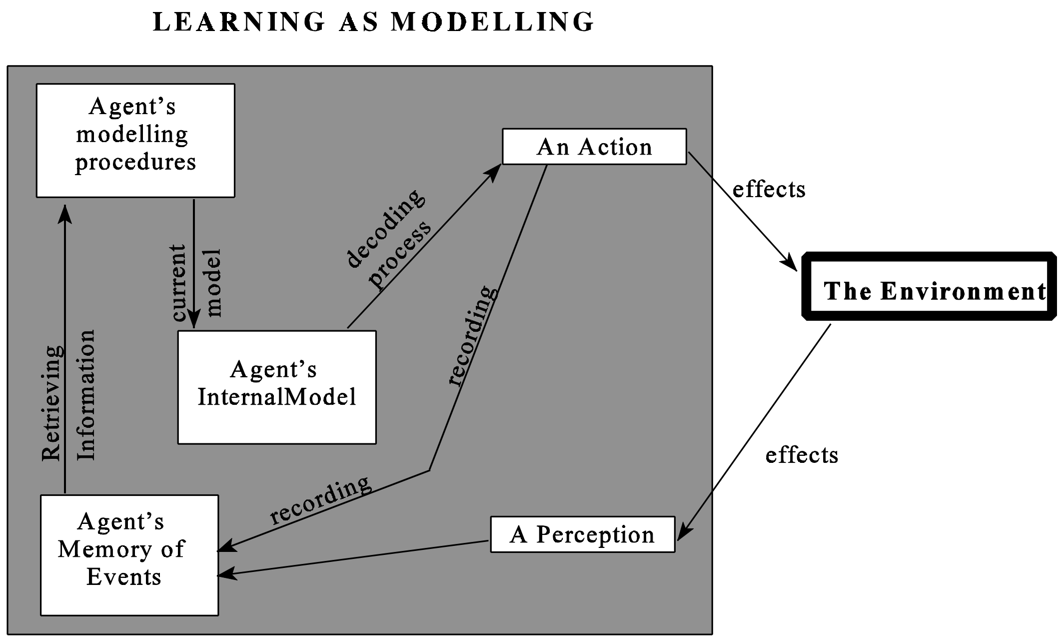

Figure 2: Information flows in learning procedures. Edmonds and Moss (1998)

Agent Architecture and Programming Language

The classical approach to build agents is to view them as a particular type of knowledge-based system (KBS). There are three generic architectures:

❍ Deliberative architectures: they contain an explicitly represented symbolic model of the world, and the decisions are made via logical reasoning based on pattern matching and symbolic manipulation.

❍ Reactive architectures are those that not include any kind of central symbolic world model, and do not use complex symbolic reasoning.

❍ Hybrid architectures. An obvious approach is to build an agent out of two more subsystems: a deliberative one, containing a symbolic world model, which develops plans and make decisions in the way proposed by mainstream symbolic AI. And a reactive one, which is capable of reacting to events that occur in the environment without engaging in complex reasoning. In such an architecture, an agent's control subsystems are arranged into a hierarchy, with higher layers dealing with information at increasing levels of abstraction.

The SDML architecture for building agents is clearly an hybrid architecture.

A complete description about SDML can be obtained from CPM´s publications and technical reports (Moss et al. forthcoming). The following features are especially important in the programming language for agent modelling:

— It is strictly declarative, the knowledge is completely expressed in a declarative way,

— It is an object oriented language including facilities as multiple inheritance,

— There are different time levels available, and the user can define new time levels,

— Agents are completely exportable to other models,

— The rules are fired in the two ways forward chaining and backward chaining,

— It is possible to define meta-agents, so that learning is contained in rulebases and databases.

CONCLUSIONS

Psychology, sociology, and economics provide wide-ranging evidence that bounded rationality is important. Economists who include bounds on rationality achieve good predicted value with their models, as well as success in describing socioeconomic behavior, according to the nature of things, beyond the range of standard neoclassical theory.

We have argued that economic modelling under bounded rationality should adhere to human cognitive limitations, as an scarce resource, as well as the social and institutional dimension of the economic activity. That economic modelling has to be done in a Multiagent System setting.

We defined an intelligent agent which is resource bounded rational and accommodates the above dimensions by importing ideas from AI. We showed how to design a MAS based upon a CPM Agent that under the SDML can be very useful in building economic models with predictive value and socially focused. Of course, the particular context of application will dictate the proper conditions under which an MAS will be used: complexity, deliberation and search cost, experience, and market discipline (the institutional veil).

We think that the application of MAS to economic modelling, under the lines we have pointed out, will be a novel, promising and fascinating field of research.

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