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Modelling Learning and R&D in Innovative Environments: a Cognitive Multi-Agent Approach

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Abstract

Evolutionary arguments are an appropriate approach to the analysis of industry dynamics in a knowledge-based economy, because they can deal properly with innovation processes, technological change, path-dependence and knowledge. But in order to formalise all of this verbal accounting, researchers need methodological tools which support their theoretical analysis. In this paper we suggest some of the main requirements for computer simulation to have the same standing as the traditional tools used by neoclassical economists. Among others, aggregated behaviour should emerge from micro-foundations, economic agents should exhibit bounded rational behaviour, learning must be endogenous and human learning should be in agreement with some stylised facts from cognitive science and psychology. We argue that multi-agent systems is a methodology which fulfills some of the requirements above. We also propose an alternative way for modelling cognitive learning in evolutionary environments, which is in agreement with some basic concepts from cognitive science. Agents are endowed with both declarative and procedural knowledge. We have used our approach to build evolutionary models of innovative industries, where firms learn how to change their decisions about R&D budget, production, technology, etc. We refer as well to some applications using the same framework to model behavioural financial markets, economic geography and water resource management.

Keywords:
Evolutionary economics, agent-based, muti-agent systems, innovation, research and development, industry evolution, knowledge-based economy

Introduction

1.1

Neoclassical theory exhibits some difficulties to explain innovation phenomena, and the roles of technology and R&D in the evolution of industries. It conceives the firm as a "black box" which transforms inputs (capital, human resources, raw materials, etc.) into outputs (profits, products, etc.), for a particular technology. Technology is exogenous to the system; it is seen as the manna from heaven. All the companies are similar (representative firm) with similar knowledge, technology and organisation.

1.2

In our understanding, evolutionary economics is a more promising approach for analysing some issues in industry dynamics because research, innovation and technology are, in essence, evolutionary processes.

A framework for modelling innovation and technology in a knowledge based economy

1.3

Evolutionary economics allows us to deal with the heterogeneity of firms, technologies, behaviours, capabilities, knowledge, etc. Innovation assures that new heterogeneity is introduced in the economic system, and the innovation itself plays a critical role in the competition between firms, and in the development of nations and regions.

1.4

Firms are conceived as processors of knowledge. Within the companies, knowledge is developed, transformed and diffused inside and outside the boundaries of the firm.

1.5

Firms exhibit bounded rationality and are endowed with some capabilities; they also have to learn to adapt to a changing environment, and the market selects and awards the most adapted companies. The actions that a firm can perform in the future depend on its knowledge and capabilities; but these capabilities are also the consequence of past capabilities and decisions. So history matters and path-dependence phenomena can be explained naturally within the evolutionary framework.

1.6

On the other side, industrial districts and clusters show us the importance of spatial issues in order to understand industry evolution. Moreover, the new economic geography emphasises the role of increasing returns to scale, transportation costs and demand in the emergence of agglomeration economies and the development of regions and countries.

1.7

Economic geography and evolutionary economics are closely related in industry dynamics and, as suggested by Boschma and Lamboy (1999), both fields can benefit from each other in the understanding of the evolution of innovative industries. Key evolutionary concepts as routines, path-dependence, increasing returns, chance and selection may be incorporated in the field of economic geography. Opposed to explicit knowledge, the diffusion of tacit knowledge needs local interactions among agents. As expressed by Freeman (1994) the origin of many innovations comes from informal conversations between scientists and entrepreneurs, clients and suppliers, colleges, etc.

1.8

However, in order to increase the power of the evolutionary arguments above, it is necessary to have a methodological framework which allows us to translate theories into models that could be replicated for validation.

1.9

Traditionally, neoclassical economists have benefited from mathematical calculus, to formalise their arguments. In this way, they have been able to build rigorous stylised models about the behaviour of firms, markets and consumers. However, as suggested by López, Hernández and Pajares (2002), the economists should search for complementary methodologies which allow them to deal with more realistic agents.

1.10

Thus, evolutionary economics needs tools with the same standing as the methodologies used by the neoclassical ones. Keynes and Schumpeter were born during the same year. But the ideas of the former were quickly incorporated into mainstream economics, perhaps because of the analytical tools he used, whereas Schumpeter's ideas were only expressed as verbal accounting.

1.11

Nelson and Winter (1982) and many others since them, advocated the use of computer simulation in order to design, build and run dynamic evolutionary models. In particular, much of the evolutionary verbal accounting can be implemented by means of computer simulation models with aggregated behaviour emerging from micro-foundations.

Purpose of the paper and organisation

1.12

In this paper we have a double purpose. In the first place, we explain some of the features that the simulation tools used for evolutionary modelling should have, if we want those methodologies to have the same standing as most of the traditional tools used by neoclassical economists. Then, we argue why multi-agent systems is a methodology that fulfills most of those requirements for economic modelling.

1.13

In the second place, we recognise the role of learning in evolutionary modelling, and we suggest how to endow agents with cognitive learning, that is, learning procedures which include some ideas from cognitive science and psychology. In our opinion, this methodology could complement previous works in which genetic algorithms, neural nets or ad hoc procedures are used to reproduce learning.

1.14

This paper is organised as follows. In section 2, we explain some of the features for simulation to be a suitable tool for evolutionary modelling of industries in the knowledge based economy. Then we advocate the use of multi-agent systems, and we explain some of the features of several multi-agent shells.

1.15

In section 3, we suggest how to include cognitive learning in the models. We endow agents with both declarative and procedural knowledge. Agents in the model learn by means of exploration, exploitation of knowledge and imitation.

1.16

In section 4, we summarise the main features of our approach and we describe some models we have built using the methodology we propose: evolutionary models of innovative industries, where firms learn how to change their decisions about R&D budget, production, technology, etc; an artificial stock market with bounded rational investors; and water resource management for the metropolitan area of Barcelona. We finish with the relevant conclusions.

Towards a methodological framework for evolutionary modelling

2.1

Neoclassical arguments usually benefit from the power of mathematical calculus. Although most of them are grounded on extreme hypotheses, the use of analytical tools gives rigour to the economic thinking.

2.2

But as we have seen above, most evolutionary arguments about innovation and technology are grounded on verbal accounting. So, we need some tools which help us to formalise all of this verbal accounting.

Neoclassical versus evolutionary modelling.

2.3

Most of the neoclassical analyses are grounded on strong hypothesis about the rationality of economic agents. In a world with perfect information, agents try to maximise some utility function, under some budgeting constraints. In this way, the economic problem can be translated into an exercise of mathematical optimization; calculus can be easily applied, and the solutions express how the behaviour of those rational agents must be, and the equilibrium relations between the most important variables in the system.

2.4

Examples of this kind of reasoning can be found inside and outside industrial economics. For instance, the Capital Asset Pricing Model (CAPM) in financial markets, is built under the hypotheses of market efficiency, rational expectations, and fully rational agents. The financial dealers want to maximise their expected return for a given level of risk. The solution of this optimisation problem gives us the popular CAPM equation, which shows how much return a dealer must demand for the level of systematic risk he/she takes.

2.5

The same kind of reasoning underlies the typical Perfect Competition Market. There, firms have to maximise their profits. Production function is known for mainstream technology, and the market clears the demand. The solution of the maximisation problem tells us that companies have to produce the quantity that assures that the price equals the marginal costs. Again, the hypotheses are translated into a maximisation problem, and its solution gives us the expected rational behaviour of the agents.

2.6

Contrary to neoclassical thinking, evolutionary reasoning is much grounded on micro-foundations about the behaviour of the economic agents and the relations between them.

2.7

Economic agents exhibit bounded rationality, and they take their decisions based on imperfect information. They learn and they have their own rules of behaviour. Aggregate behaviour emerges in the system as a consequence of the interactions among all the individual behaviours.

2.8

To capture this emergent behaviour, computer simulation is used in order to design, build and run dynamic evolutionary models. In figure 1, we represent the difference between neoclassical models and simulation.

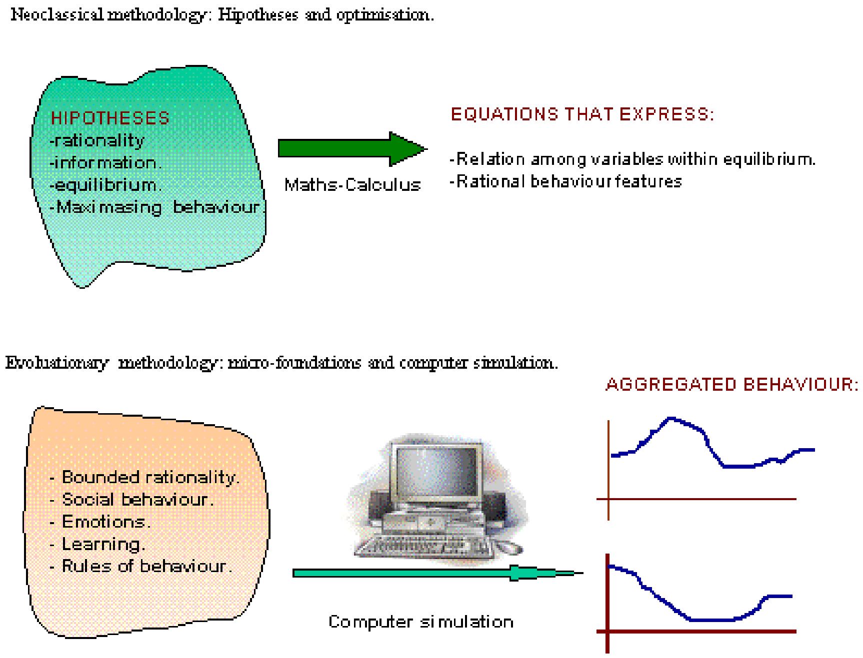

Figure 1. Neoclassical and evolutionary methodologies

Simulation tools for evolutionary modelling: main requirements

2.9

Dating back to the first models proposed by Nelson and Winter in the early eighties and up until today, computer science has changed as few other fields of knowledge have done. Of course, the power and speed of the computers have increased. But also, the software facilities have changed a lot.

2.10

Gilbert and Troitzsch (1999) show the different methodologies available for simulation in the social sciences. They also show how social simulation can be applied to a large number of socioeconomic problems. Neural networks, genetic algorithms, muti-agents systems and cellular automata are only examples of the tools available for simulation in economics.

2.11

The methodology chosen depends on the special features of the problem we want to analyse and the purposes of the simulation. Taking into account the features of the process of innovation explained earlier in this paper, we suggest that a suitable tool for modelling innovation and technology should fulfill, among others, the following features:

- It must allow to build models grounded on micro-foundations, that is, using the bottom-up approach. As explained before, the inputs of the evolutionary models are the agents' behaviour, whereas the outputs are the aggregate behaviour of the system.
- Bounded rationality of firms, consumers and institutions must be easily implemented in the models. The methodology should allow to implement both substantive and procedural rationality in the sense of Simon (1987).

- The role of knowledge in evolutionary modelling of innovation, research and technology development has been emphasised earlier in this paper. A suitable tool should allow us to endow agents with knowledge about the environment where they live, about the possible consequences of their decisions, and about the way to solve the problems they face. Both explicit and tacit knowledge must be implemented.
- Learning is at the heart of any evolutionary argument. From an evolutionary perspective, learning can be conceived as the process of searching and election among different alternatives. A suitable tool for evolutionary modelling should allow us to implement this process.
- Human beings are the subject of learning. So, as we will suggest later on in this paper, learning in evolutionary models should be in agreement with the most important facts about human cognition.
- As explained in previous paragraphs, an important piece of knowledge comes from local interactions between agents. So, the software device used for evolutionary modelling should allow us to implement without diffculty both agent communication and agent interaction. In this way, we will be able to implement the features of the National Innovation Systems framework, clusters and industrial districts.
- The role of spatial issues in technological change and regional development has been commented earlier on in this paper. So the simulation tools should allow us to model in a friendly way the behaviours of agents located in specific points of the space. A grid-based simulator could help.
- Human behaviour can be easily implemented in a computer by means of rules with antecedents and consequents. If the former are true, then the consequents are also true. So a rule-based methodology should be appropriate.
- At any point in time, several rules could be true, with the consequent conflict between them. A logic underlying the rule-based system must exist as well as a logic that makes assumptions and resolves them, so that the firing rules order is coherent with this logic.
- Emergence: Aggregated behaviour should emerge from the behaviour of individual agents. Emergence means that it is possible to find aggregated behaviour that is not foreseen ex-ante, given the individual behaviour.
- Emergence is a very important issue in social simulation, because it assures that we can obtain real substantive knowledge and understanding from simulations. If we can only simulate predictable events, simulation becomes senseless.
- A powerful graphical interface should allow us to draw the most important variables concerning both the aggregated behaviour of the economic system and the individual behaviour and performance.
- Friendly computer tools. Its quite difficult to be an expert in both economics and computer science. The difficulty in programming evolutionary models in computer programs represents one of the highest entry barriers for an economist to join the evolutionary modelling community. Moreover, probably more mainstream economists would embrace evolutionary arguments if we could provide them with friendly simulation tools.

Multi-agent systems for evolutionary modelling

2.12

In our opinion, the simulation approach that best fulfills most of the requirements above is the multi-agent systems. It is an intuitive way to translate the agent behaviour into computer language. Multi-agent systems is a methodology included within the Distributed Artificial Intelligence (DAI).

2.13

An agent is a computer system, situated in some environment, that is capable of flexible autonomous action in order to meet its design objectives (Jennings, Sycara and Woolridge 1998).

2.14

A multi-agent system includes several autonomous, heterogeneous and independent agents, each of them interacting with the environment and with other agents. Multi-agent systems have been successfully used in manufacturing, process control, telecommunications, air traffic control, transportation systems, information management, electronic commerce, business management, and health care monitoring.

2.15

For our purposes, in economic simulation, a multi-agent system allows us to concentrate on the programming of the individual behaviour of the agents, and the multi-agent system has the responsibility to generate the aggregated behaviour. So, multi-agent systems are quite intuitive to implement a bottom-up approach in economic models.

2.16

Most multi-agent languages are rule-based. This means that the behaviour of the agents is implemented by means of rules. In this way, it is easier to implement bounded rational behaviour, the agent's knowledge, learning procedures, etc. Multi-agent systems usually have specific protocols of communication between agents, so that interactions can be implemented.

2.17

A number of agent simulation toolkits is now available. Some shells have been specifically designed for social science simulation purposes. Of course, we do not want to be exhaustive. We only want to give the reader an idea of the different shells that are available.

- *Swarm* is one of the most famous agent-based environments in social science research. It was developed by Nelson Minar and Chris Langton at the Santa Fe Institute. Swarm is a collection of libraries, written in Objective C. It has friendly graphical tools such as graphs, windows, and input widgets.
- *Repast* (Recursive Porous Agent Simulation Toolkit) was developed by the Social Science Computing Group at the University of Chicago. It provides Java Language libraries of classes for creating, running, displaying and collecting data from agent based simulation. It can also create movies of the simulations. It operates in much of the same way as the Swarm libraries, and could be properly term "Swam-like".
- *Ascape* was developed by Joshua Epstein and Robert Axelrod at the Brookings Institution. Ascape is a flexible tool, operating in much the same way as Swarm and Repast. Agents live within scapes: collections of agents such as arrays and lattices. These scapes are agents themselves, so that typical Ascape models are made up of "collections of collections" of agents. Scapes provide a context for agent interaction and sets of rules that govern agent behaviour. It manages graphical views and a collection of statistics for scapes and provides mechanisms for controlling and altering parameters for scape models.
- *StarLogo* is a programmable modelling environment for exploring the behaviours of decentralized systems, such as bird flocks, traffic jams, and ant colonies. It was developed by Mitchell Resnick at the MIT Media Lab and it is an extension of the Logo programming language.
- *SDML* (Strictly Declarative Modelling Language) was developed at the Centre for Policy Modelling, Manchester Metropolitan University. The main features of SDML can be found in Edmonds, Moss and Wallis (1996) and Moss et al. (1998).

2.18

In the Social System Engineering Group at the University of Valladolid (Spain), we have used SDML, JAVA and Swarm for economic simulation purposes. We have used SDML for modelling innovative industries (Pajares, Hernández and López 2003), auctions and bargaining (López, Hernández and Pajares 2002). We have used the JAVA-SWARM approach for building models of financial markets, in order to explain some financial anomalies (Pajares et al. 2003).

2.19

Some features of SDML make it specially suitable for evolutionary cognitive modelling. In particular, SDML is a strictly declarative language. This means that it has no imperative elements. The designer of the model has to write the initial knowledge that the agents have and the rules that express what is true in the system. Each agent has its own rule-bases and databases, where all its knowledge can be stored.

2.20

The databases record the facts that define the state of the agent, its knowledge and beliefs. Rules have antecedents and consequents. If the former are true, the propositions of the consequent are also asserted as true in the databases; as rules trigger, the consequents change, and the antecedents of other rules become true, so that other rules can trigger. In this way, the system evolves over time.

2.21

The logic of SDML's propositional inference engine is equivalent to a fragment of the Konlige's strongly grounded autoepistemic logic (SG-AE). (Edmonds, Moss and Wallis 1996). This logic supports reasoning with introspection, that is, the ability to reason about one's own beliefs; so it is suitable for cognitive modelling.

2.22

JAVA is a widely used language for general programming purposes, and it allows to export models from one machine to another. In the Social Systems Engineering Group at the University of Valladolid, we use JAVA in combination with SWARM.

2.23

In this way, we can benefit from the advantages of JAVA and from the power of the agent based libraries of SWARM. In particular, we build programs which include one module with the model itself and another module with the "observer". We also benefit from the powerful graphical features of SWARM.

Cognitive learning and evolutionary modelling

3.1

Generally speaking, we could agree that learning has not been widely considered in mainstream economics. If agents are rational, they have all the knowledge and all the information they need.

3.2

Under the Rational Expectations Hypothesis, economic agents know the model of the world, and the relations of the economic variables of their interest. Under this framework, learning is not the main issue.

3.3

In the Theory of Rational Choice under Uncertainty, the agents have to choose the alternative with highest utility (or profit) among a set of alternatives. The agents know the distributions of probability of the different facts of nature, so they just face a problem of optimisation under uncertainty. Again, learning does not get the appropriate dimension.

3.4

But, in real and evolutionary environments, agents have to learn because (Dosi, Marengo and Fagiolo 1999): they have an imperfect understanding of the world in which they operate; they master only a limited repertoire of actions in order to cope with the problems they face as compared to the set of actions that an omniscient observer would know; and they have only a blurred and changing understanding of their goals and preferences.

3.5

This means that, within evolutionary arguments, agents exhibit bounded rationality, and they have to learn to adapt themselves to the changing and imperfectly known environment; they have to change their decisions over time depending on their previous knowledge and on the feedback they receive from the result of their past decisions.

3.6

For this reason, in evolutionary economics, learning is a central issue of every model, and consequently, all the models must include some kind of "software device" that implements how agents learn.

3.7

Some models in the evolutionary literature include ad hoc learning, usually by means of rules of thumb that reproduce some well known entrepreneurial behaviour. But other models try to make the learning process endogenous. For this aim, learning is usually seen as a process of **discovery, search and election** among the different alternatives that agents face. Perhaps for this reason, some evolutionary models have included some tools which had been traditionally used with success in Artificial Intelligence, mainly for heuristic forecasting and optimisation purposes. This is the case, for instance, of genetic algorithms, genetic programming or neural nets.

3.8

Thus, Kawasnicki (1996) and Yildizoglu (2002) among others, use genetic algorithms to model how firms learn to fix their R&D budget. Oltra and Yildizoglu (1998) and Yildizoglu (2001) propose neural networks as learning devices that allow agents to form expectations. Dosi et al. (1999) showed how genetic programming can be successfully used to model learning in industrial environments.

3.9

Of course, all these tools allows us to introduce useful learning behaviour in the models. It is, nevertheless, quite natural to complement these works by looking at what cognitive theories have to say about learning.

3.10

For this purpose, in this paper we have introduced an alternative way to model learning in evolutionary environments, regarding some well known facts about the process of human learning and human cognition. Specifically speaking, we have included some relevant features from cognitive science, and we have endowed the economic agents with declarative and procedural knowledge.

3.11

We are not pretending to become experts in cognition, cognitive architectures or knowledge storage; we are just borrowing some general principles that are widely accepted in cognition theory, so that we can design more realistic agents in order to achieve more realistic models.

Cognitive learning for evolutionary environments

3.12

Cognitive science is the interdisciplinary study of cognition. And cognition includes mental states and processes such as thinking, reasoning, remembering, language understanding and generation, visual and auditory perception, learning consciousness, emotion, etc. (Rapaport 2000).

3.13

Cognitive science has arisen at the intersection of a number of existing disciplines, including psychology, linguistics, computer science, philosophy and sociology. Understanding the nature of the mind has been the common interest leading to this "coalition" of fields. Previously, each discipline sought to understand the mind from its own perspective, benefiting little from the progress in other fields. With the advent of Cognitive Science, shared interests and theoretical ideas have overcome methodological differences, and interdisciplinary interaction has become the hallmark in this field.

3.14

In relation to our methodology, we have to remark that the field of Cognitive Science is closely related to Artificial Intelligence. Cognitive scientists study the nature of intelligence from a psychological point of view, usually building computer models in order to understand what happens in our brains during problem solving, remembering, perceiving, learning, and other psychological processes. One major contribution of both Artificial Intelligence and Cognitive Science to Psychology has been the information processing model of human thinking in which the metaphor of "brain-as-computer" is taken quite literally.

3.15

Cognitive science and cognitive psychology show that humans learn by means of exploitation and exploration of knowledge, and imitation of other agents. Most of the time, humans **exploit** past knowledge; when some strategy works, they usually repeat the same set of actions under similar conditions. Agents also **imitate** other agents, especially the behaviour of those agents with a good performance; and when humans face a new situation where any of the last strategies has worked, they **explore** new options and innovate.

3.16

Most of the ideas from cognitive science can be implemented by means of cognitive architectures, as SOAR (Newell 1990, and Laird et al. 1987) and ACT-R (Anderson 1993). From them, we have taken the important distinction between *declarative* and *procedural* knowledge.

3.17

Declarative knowledge can be explained verbally to other people. Sentences as "Madrid is the major city in Spain" or "after raining, it is cooler" are examples of declarative knowledge, although the degree of certainty about both propositions could be quite different.

3.18

By procedural knowledge, we mean knowledge that cannot be transmitted verbally, so that it can only be observed when an individual who has this kind of knowledge exhibits it in practice. For instance, a doctor is using procedural knowledge when he/she diagnoses his/her patient's disease based, not only on academic knowledge, but also as a result of his/her accumulated experience as well.

3.19

Sometimes, the border between declarative and procedural knowledge is not fixed. The same knowledge can be implemented in one way or the other depending on the context. Moreover, due to repetition and experience, declarative knowledge can become procedural. For example, an expert pianist knows exactly the position of every key on the keyboard (declarative). But when the pianist is playing a difficult score by Chopin, he/she has to use procedural knowledge to play it. After hundreds of repetitions, the declarative knowledge has become procedural.

3.20

The agents in evolutionary models must be endowed with both declarative and procedural knowledge. The former corresponds with models of the world, beliefs about the relations between the relevant variables, facts of the environment and the behaviour of other agents. The rules and strategies that the agents can use depending on the features of the environment are also declarative knowledge. For instance, if an agent believes that profits and R&D expenditure move in the same direction (an increase in the level of R&D expenditure will lead to higher profits), then the agent will play a strategy in order to increase R&D investment next period.

Modelling procedural knowledge. Endorsement schemes

3.21

Procedural knowledge can be modelled as the non-verbal processes that agents use to change their beliefs about the certainty of the models of the world or about the goodness of a strategy. Thus, procedural knowledge will be modelled as a change in beliefs.

3.22

Of course, it is possible to build a lot of methodologies to model beliefs and changes in beliefs, but one of them has to be chosen. The alternative we use, the endorsement scheme, is grounded on a methodology proposed by Cohen (1985), which agrees with empirical evidence from cognitive sciences. Endorsements have also been successfully used by Moss (1995) and Moss (1998) for economic modelling purposes.

3.23

An endorsement is a data structure that summarises the reasons to believe or not to believe in the propositions the endorsement is related to. Thus, endorsements give us a measure about the degree of confidence we have about the certainty of a proposition. For instance, our confidence about the certainty of the proposition "after raining, it is cold", depends on the geographical area where we live, if we are dry or wet after raining, and about our individual feeling about what is cold or warm weather.

3.24

Not all the reasons to believe in something have the same weight in the final certainty about the proposition. As a consequence, a hierarchy of classes has to be defined, so that, endorsements in the same class have the same degree of certainty. Furthermore, a scheme of weights must be established, in order to assess the number of lower class endorsements that are equivalent to one endorsement of a higher class. Finally, a measure of the belief is built, based on the total endorsement, which is computed considering all the weights of all the classes associated with the propositions that are true.

3.25

A simple example should help to understand how endorsement drives learning. Suppose the (probably non-verbal) process of choosing a restaurant to have dinner with some friends on Saturday night. Usually, there is in our mind a portfolio of possible restaurants, formed with the most endorsed ones, that is, the restaurants that were more pleasant in the past (exploitation of knowledge).

3.26

As it happens, this portfolio does not remain unchanged over time: some restaurants can exit the portfolio because we had an unpleasant experience one night; others can enter the portfolio because a colleague has recommended it (imitation); sometimes, we want to try something new and we go to a restaurant never chosen before (exploration and innovation).

3.27

The endorsement scheme is generated from the reasons to believe that a restaurant is pleasant and the weights associated to each one. For instance, we can consider some common reasons for assessing how good a restaurant is; if it is cheap and if you do not have to wait too long to get a seat. But perhaps, a stronger reason is that the food is excellent. Then we can assess, for instance, weight 1 to the former reasons (lower class endorsement) and weight 2 to the last one (higher class). Negative weights are also allowed, if we have reasons to believe that a restaurant is not pleasant. For instance, we can assess weight -2 if the restaurant is too crowded and noisy. In table 1, we summarise the endorsement scheme.

Table 1: Endorsement scheme for the restaurant example

Weight	Endorsement	Explanation	Example
2	Food	The food is excellent	$2^2 = 4$
1	Price	The restaurant is cheap	$2^1 = 2$
	Time	You do not have to wait long	-----
-1	Crowded-Noisy	Too crowded and noisy	$-2^{abs(-2)} = -4$

		Total endorsement:	4 + 2 - 4 = 2

3.28

In order to compute the total endorsement, we use a similar procedure to the one employed by Moss (1998). First, we have to choose a base level, which indicates the number of times that an endorsement of a lower class is equivalent to one endorsement of higher class. Suppose we choose a base value of 2 for this case, and suppose that in a particular restaurant we have the evidence that it was cheap and the food was excellent, but it was very noisy. In this case, the total endorsement will be 2 as shown in the right column of table 1, computed as the sum of the base level 2, powered to the absolute value of the weight of the propositions with evidence. In the case of negative weight, we must subtract the powered quantity instead of adding it to the total endorsement value.

3.29

In evolutionary modelling, we use the endorsements to endow the agents with an idea about the certainty of different models of the world and the goodness of some strategies. In this way, the evolution of the endorsements over time leads the cognitive learning process of the agents.

3.30

We want to emphasise again that alternative ways of modelling procedural learning could be designed. The one we propose here is just one of them, as far as we know, coherent with some ideas from cognitive science.

Putting cognitive multi-agent modelling to work: futures challenges

4.1

The methodology we have used for modelling evolutionary environments is grounded on relevant ideas from evolutionary economics, artificial intelligence, agent-based computational economics, multi-agent systems and cognitive science (see figure 2). Multi-agent systems belong to the field of distributed artificial intelligence, and allow the modeler to concentrate on individual behaviours of the agents.

4.2

Agent-based computational economics deals with the behaviour of complex economic systems by means of bounded rational agents. We can get a better understanding about the relations between micro-foundations and the aggregate behaviour of complex systems and we can also explore under what conditions micro-complexity cancels itself at the aggregate level. New and not foreseen ex-ante behaviour should emerge running the models.

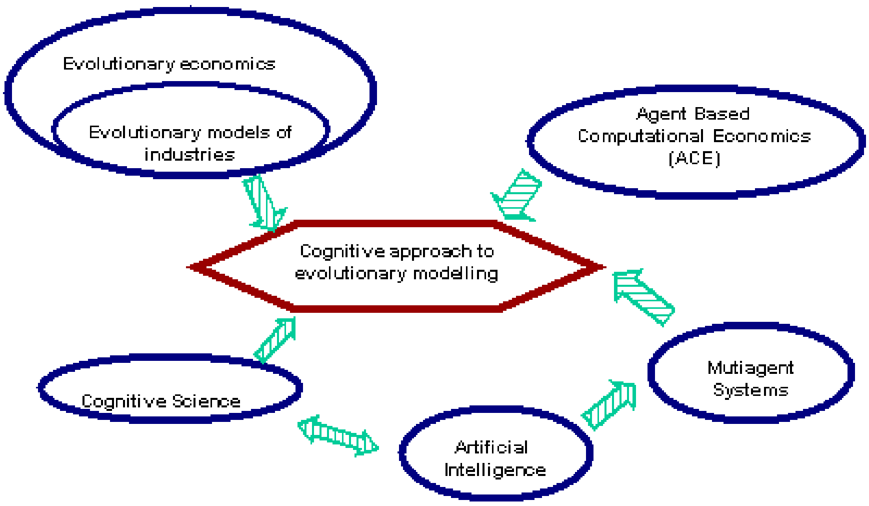

Figure 2. The cognitive multi-agent approach to evolutionary modelling

4.3

Artificial intelligence has used some of the relevant ideas from cognitive science in order to implement "real human behaviour" in computers; but, at the same time, some formalisms from artificial intelligence have inspired the structure of cognitive architectures.

4.4

Evolutionary arguments help us to think in terms of diversity, selection and path-dependence. Bounded rational agents learn to change their decisions over time in order to adapt themselves to a changing environment.

4.5

The framework drawn in figure 2, was initially designed for modelling the evolution of innovative industries, translating evolutionary theoretical arguments into models. However, later on we realised that the same framework could be successfully used to model other kinds of systems. Now we are going to summarise the most promising ones.

A cognitive multi-agent model of industry life cycle

4.6

In Pajares, Hernández and López (2003) we show the main features of an evolutionary and cognitive industry model, using the multi-agent platform SDML. Our main purpose with the model is to reproduce the stylised facts in industry dynamics, about entry, exit, concentration and innovation patterns, as summarised by Klepper (1996). Furthermore, empirical phenomena in industry dynamics like path-dependence, knowledge spillovers and externalities are included in the model.

4.7

We also show that within this framework, it is possible to model R&D and the appearance of new technologies. Innovation and R&D is the driven force of industrial change, and firms must learn cognitively how to adapt their expenditures in both product and process R&D. To do that, they look not only at the results of their past decisions, but at the performance of successful competitors as well.

4.8

Following the tradition in product life cycle industrial models, we have considered both product and process innovation. In every period, two products are traded in the market: one of them is related to an obsolete technology, whereas the other is more recent and technologically superior.

4.9

When the firm's product innovation succeeds, a newer product will be demanded, and the most obsolete product will disappear (the previous recent product becomes the old one). The aim of process innovation is to improve production in order to reduce manufacturing costs and to increase productivity. Products and technologies are related in the model, so each product is manufactured with a different technology.

4.10

Firms are the main agents in the model. They decide when to enter or to exit, their production capacity for each product and the R&D policy, that is, the budget for both process and product R&D expenditures. Firms store a number of different strategies (R&D budges, production, etc.) and they have degrees of beliefs about the value of any strategy at any particular time. The evolution of the degrees of belief are modelled by means of endorsement schemes.

4.11

Every firm has a memory to store past decisions and the achieved results. That knowledge is used to endorse the successful decisions and the errors during the firm's lifespan. Firms can also imitate the strategies played by the leading companies of the industry.

Financial Stock Markets

4.12

Mainstream finance is grounded on the hypothesis of market efficiency and on the notion of rational expectations of financial dealers. Within this framework, it is possible to build nice models of market behaviour in equilibrium, like the capital asset pricing model (CAPM). However, those models can not properly explain some observed phenomena as market bubbles and excess volatility.

4.13

Recently, the term "behavioural finance" has emerged within the researchers in finance, as a promising approach to study financial markets from an alternative way, taking into account the real behaviour of investors. In order to implement much of the verbal accounting, some models have been built to explain some stylised market behaviours, as the "artificial stock market" proposed by Le Baron (2000, 2002).

4.14

In Pajares, Pascual, Hernández and López (2003), we propose a behavioural, evolutionary and generative approach for modelling financial markets. We have built an artificial stock market where a single stock is traded. Dealers can invest in this security or they can lend or borrow their money at the risk free interest rate. Dealers are bounded rational, and their behaviour is in agreement with some relevant ideas from behavioural finance.

4.15

Heterogeneity of strategies is allowed and analysed under different market conditions. Some agents behave close to rationality, as neoclassical finance suggests; other investors change their aversion to risk depending on the evolution of their wealth, as suggested by Kahneman and Tversky (1979); we also include trend followers and dealers whose buying and selling decisions are taken randomly.

4.16

At any period of time, each investor has to decide, within some budgetary constraints, the number of shares he/she wants to buy or sell and the amount of money to lend or to borrow at the risk free interest rate. Investors send their demands to a specialist who plays the role of a clearing house. The specialist does not trade shares at all, he/she just computes the price that clears the market, according to the bids and asks received. We should emphasise here that price is not exogenously fixed, but emerges as a consequence of the interactions and expectations of the investors.

4.17

The stock traded pays dividends at the end of each period. The amount of dividends changes over time and is unknown by the agents, although it can be changed exogenously by the modeler, so that we can study the response of the market to structural changes.

4.18

Path-dependence in terms of patterns of successful strategies emerges in the model. We also explore some stylised evolutionary patterns in financial markets. The model has been implemented in JAVA, although it uses some routines from SWARM.

4.19

We use the model in order to get a deeper understanding about one of the most widely studied anomalies in financial economics: the volatility puzzle. In essence, this anomaly says that the volatility of the stocks (or a portfolio of assets representing an index) is higher than the theoretical value suggested from the efficient market hypothesis.

4.20

From the results of our simulations, we suggest that there is a strong relationship between the degree of "irrationality" in market agents and market volatility.

Spatial Economics and Economic Geography

4.21

The importance of the spatial dimension in the evolution of industries has been deeply emphasised within this paper. The utility of the agent-based approach to model the location decisions of both firms and households was shown in Otter, van der Veen and Vriend (2001).

4.22

In our opinion, the cognitive multiagent approach can also be adapted to deal with other regional problems studied by Economic Geography and Urban Dynamics. For instance, in Saurí et al. (2003), a model of freshwater resource management for the Metropolitan Area of Barcelona has been proposed. Citizens have to decide on their consumption of water and they can move from one area of the city to another, depending on their incomes and preferences. The model includes climate and geographical issues concerning the real metropolitan area of Barcelona, and social and economic issues, related to the citizens' behaviour.

4.23

The complexity of the problem arises from the different (and sometimes opposite) aims of the agents in the model: citizens, municipalities, house builders, neighbourhood unions, water facilities, weather conditions, and the Government of the Autonomous Region of Cataluña.

4.24

Several scenarios are analysed under different patterns of growth of the metropolitan area, and under different future weather conditions. The model is used to suggest a wide range of water management policies.

Conclusions and future research

5.1

Evolutionary arguments are a suitable tool for analysing industry dynamics in a knowledge based economy. Moreover, evolutionary thinking can be complemented with some relevant ideas from economic geography and knowledge management.

5.2

However, many of these arguments are grounded on verbal accounting. In this paper we have suggested some features of a methodology which allow evolutionary economists to formalise models in computers. We advocate multi-agent systems, although we are aware that other solutions could also be suitable.

5.3

By means of multi-agent systems, the modeler can concentrate on programming the individual agent behaviours and their interactions. Then, aggregated behaviour emerges during the simulation in run time.

5.4

Learning is one of the most important features of an evolutionary model. In this paper, we have proposed a slightly different way to model learning. Our aim is to include some relevant stylised facts of human learning, as explained by cognitive science and psychology. We endow agents with both declarative and procedural knowledge, and agents can learn by means of exploration and exploitation of knowledge, and imitation of other agents.

5.5

We agree that alternative ways for modelling cognitive learning can be suggested. The methodology we propose here is just a first attempt to introduce cognitive features in evolutionary models. Furthermore, we encourage evolutionary economists to develop alternative "mechanisms", also in agreement with cognitive science.

5.6

The methodological approach we suggest in this paper has been successfully used to build models of industries, reproducing some of the empirical stylised facts of the evolution of innovative and high technology sectors. But our approach is also useful for modelling financial markets, economic geography issues and water resource management.

5.7

In all of the cases, we are able to reproduce the main stylised facts about the system we want to analyse; our bottom-up approach allows us to get better understanding of real phenomena.

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