theory, risk-adjusted rewards, reinforcement learning, and the balance between exploitation and exploration. This research trend can be generally thought of as a mapping from the brain space to the decision or behavioral space in the sense that a single decision or type of behavior can be mapped to a sequence of temporal and space images of brains. What software-agent designs attempt to do is not very much different except that the mapping is from the decision or behavior space to a space of algorithms. Hence, ACE, EE and NE are closely related as shown in Figure 1.

Conclusions: The Future of Agents in Economics and the Social Sciences

Based on the interdisciplinary framework as summarized in Figure 1, we show how the integration of the three branches of economics can constitute a new framework for the next step on the economic research agenda. Part of this new framework is a laboratory composed of both *human agents* and *software agents* and allowing for the interplay between the two as illustrated in [27]. In this lab, computational intelligence still plays the role of designing software agents, just as it has done for ACE before. Nevertheless, the integrating framework may change the nature of the design. Even though intelligence or intelligent behavior remains an important goal of the design, it is not the only consideration. In some cases, agents with emotional designs or *emotional agents* can be just as important as intelligent agents. In other cases, even though agents are all intelligently designed, we need to differentiate them in terms of their degree of intelligence as human agents are heterogeneous in their intelligence quotient (IQ). Therefore, the new framework enriches the design of agents. It is no longer just narrowly restricted to computer science, but more broadly connected to cognitive psychology, behavioral genetics, neural sciences, and social sciences. These extended software agents provide us with better robustness tests of various institutional or market designs [28].

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Computational Intelligence in Economic Games and Policy Design

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Introduction

Computational intelligence (CI) techniques become more and more important for seeking solutions, strategies, or aggregate behaviours in economic games. By economic games, we mean games that have their foundations in game theory with an economic setting or market models in micro-economics that can be formulated as (elaborate) games. Examples of the former are negotiation, auction, and the prisoner's dilemma, while instances of the latter are basic models like the Cournot oligopoly game or elaborate models for electricity and labor markets.

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A variety of CI techniques has been developed and applied for economic games, in basic forms or for their extensions. Often, the relevance of CI techniques starts where the analytical or mathematical approaches appear to end. This varies form realistic extensions of basic games to complex game models that try to mimic reality as closely as possible. Examples of the former are changing parameters in the Cournot oligopoly game and incomplete information about opponents in a negotiation, while examples for the latter include models for electricity and labor markets. The CI techniques that are appropriate for studying economic games vary from games to games, and range from evolutionary algorithms (EAs), neural networks (NNs) and graphical models to reinforcement learning (RL) and fuzzy systems (FS).

Research in the above areas is typically performed in the disciplines of computer science (CI, agent systems, machine learning) and economics (computational economics, complex adaptive systems).

In this short article, it is impossible to give a complete overview of the entire field. We will give some highlights of the field according to our personal interests and show the importance of CI techniques for economic games and policies.

CI in Game Strategies and Game Simulations

The types of problems that are dealt with here are either the development of strategies of individual players (agents) in the game or the study of the aggregate behaviour of all players together in the game (market behaviour). In both cases, the strategies that players play in the game have to be represented in some way and learned by means of CI techniques. Examples include chromosomes that contain explicit bids for auctions (learned by EAs), general bidding parameters representing the speed of concession in negotiation (EAs, NNs, FS), explicit action representations in certain states of the environment (RL, EA, NN, FS), complete function representations for production strategies in the Cournot game (EAs, NNs), or classes of opponents with different strategic behaviour (NNs). Apart from the CI technique that is used, an important issue is whether agents learn on their own (individual learning) or whether they learn together as a society (social learning). For the latter, often EAs are used, since a population of strategies can be evolved that can be used from which the agents in the game can make their pick.

Strategy Development in Stylized Economic Games

As mentioned before, CI research especially focuses on (extensions of) games that go beyond analytical solutions. In particular, repeated games are the key when using CI techniques, either because repeated games may be hard to solve, or because repeated games allow for learning by CI techniques. An important example is the repeated bidding in auctions. Although some decision theoretic approaches exist for some cases, much of the theory on one-shot auctions does not hold any longer as soon as a sequence of auctions is considered from which a bidder likes to obtain one or more items. A reason for this when similar items are offered in several auctions, is that a bidder may first deliberately underbid while hoping to get a better deal then or later on. In case a bidder needs to obtain several items as an essential combination (e.g., not only a hotel booking but also a flight for the same holiday period), a bidder must obtain one item before trying to obtain another one, which raises questions about risk of failure and loss (in case not all required items are obtained) as well as the question of the exact bid values for these individual items. Good bidding strategies then much depend on the existence and behaviours of other agents in these auctions, and these vary substantially in different settings. In such cases, learning from repeated games and in environments at hand may yield good bidding strategies for a bidding agent [3], [20], [22], [21], [25], [41].


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Similarly, in playing repeated games, an agent may like to predict what the opponent will do in case the agent performs a specific action in the game; i.e., what will be the reaction of the opponent when the agent makes a certain move. An example is making a "bad" (defect) move towards the opponent in the iterated prisoner's dilemma (also see next subsection) which yields the agent more reward, but that may be retaliated by the opponent in the next game. Such prediction of action-reaction behaviour can be learned in repeated plays with one opponent, and can be used to forecast opponent reactions, even if the behaviour of the opponent is changing over time. For such individual learning in repeated games, reinforcement learning techniques are used [12], while the forecasting of action-reaction moves are learned by extensions of such techniques [25].

A different approach appears in case of complex negotiations. In complex negotiations, multiple issues are negotiated with complex interdependencies between them. An example is the negotiation about the sales of a computer: issues are e.g., the price and additional options like a screen with or without low-quality built-in speakers, high-quality external speakers, a low/high-quality sound card, and so on. Some issues exclude other issues (normally, one does not use a low-quality sound card with high-quality speakers), and other issues may enforce each other (it is nice to have both a sound card and speakers, while just the speakers may be worthless here). Graphical models can represent opponent preferences in complex negotiation, i.e. complex interdependencies between the issues. The structure of such a graph can be learned from past data with customers, giving an aggregate model for a class of customers.

During negotiation with one specific customer the graph is fine-tuned and updated to get closer to the preferences of the customer, leading to a better deal. A salesman may thus represent customer preferences for combinations of issues in a so-call utility graph [37], [38], [7].

Several other approaches to design CI solutions to economic games exist. Still, many open problems are present as of today. One of the important open problems is that of co-learning [10], [28], [27]: how can agents with their own learning abilities or techniques be implemented, how and what can they learn together, and what conclusions can be drawn in a robust way? Another one is that of how to test and evaluate learning agents in economic games in a more robust way [36]. Testing in self-play or against a number of basic opponents is standard up to now, but new and more evaluation approaches with multiple types of opponents are being considered. One recent alternative is to use a rigorous and quantitative framework to measure how well a learned strategy will perform against unseen opponents [10]. Although an accurate measure is hard to obtain for an economic game, it is possible to derive rigorous bounds on the generalization ability of learned strategies. They will help us to understand more in-depth what it means or should mean when a claim is made about an "optimal" strategy.

Strategy Learning for Repeated Dilemma Games

Among various CI techniques used for strategy learning, self-play and co-evolutionary learning are often used. For example, there has been a large body of work on evolving strategies for iterated prisoner's dilemma (IPD) games [5], [13]. The co-evolutionary approach is particularly attractive in this case because it makes no assumption about the games and can be used to simulate more realistic real world scenarios [9]. Instead of investigating 2-player IPD games, there has been work on co-evolving strategies for N-player ($N > 2$) IPD games [49], [50], which are qualitatively different from the 2-player games. Conclusions that were true for the 2-player IPD game may not hold anymore for the N-player game. It becomes far more difficult or even impossible to learn cooperative strategies using co-evolution [49].

In the real world, the number of players could be thousands or even millions. It becomes unrealistic to assume that every player would be able to interact with every other player in a game. It is also unrealistic to assume that a player can make two choices only, such as full cooperation or defection. Reputation and multiple choices (i.e., multiple levels of cooperation) have been introduced into the IPD game to capture such complications [51], [11]. CI techniques, such as co-evolutionary learning, can still be used to learn strategies for such complex games. It is interesting to find out that even a reputation with the minimal information captured by a single binary bit can change the dynamics of the co-evolution and the co-evolved strategies dramatically. It is also interesting to know that more strategic choices actually lead to more frequent mutual defection rather than mutual cooperation as one might have thought [14]. Also, one would expect that multiple levels of cooperation would encourage the evolution of mutual cooperation in the IPD game, since the loss of being defected by other players would be small and players might be more willing to try cooperation. Simulation results show, however, the opposite is true [51],[11]. This observation was interestingly linked to the National Missile Defense [15].

Simulation of Economic Markets and Adaptive Software Agent Systems

In the domain of economics, the most relevant decision makers are primarily economic policy makers, like the different levels of government, the central bank or regulatory authorities, and also individual organizations or companies, like stock exchanges or online trading platforms. A major challenge of research in economics is to provide normative advice for such decision makers that is based on the rigorous analysis of relevant models or suitable empirical data. Traditionally, the models employed to provide policy analysis and recommendations are based on highly stylized analytical models that follow a neoclassical approach and rely on rational choice theory, equilibrium behavior and the concept of representative agents (e.g., households, firms). Such models typically provide only rudimentary representations of important organizational aspects and market protocols, and they hardly capture effects stemming from decentralized interaction of heterogeneous interacting agents. Also, in order to be tractable, such models are often tailored to focus on one particular policy aspect, and little insights are gained how the effects of different types of policies interact. Many of these problems of traditional economic policy analysis can be avoided if agent based simulation models are employed to evaluate the effects of economic policy measures.

CI techniques can thus also be used and developed for simulating economic markets. The idea is that market models are either developed in a more realistic way than in theory or existing simple market models are extended. Various examples can be found in the literature, though mostly in the economics literature [39], [40]. Idea is that agents operating in a market are considered to be adaptive and to have limited reasoning capacities as well as information ("bounded rationality"). Such adaptive agents, which are considered to learn and improve their market strategies, are modeled in some form in the simulation system, where the learning capacities are implemented by CI techniques. Such techniques often are EAs, NNs and RL techniques. By running the simulation system several times, an aggregate behaviour of the market can be obtained. In such way, experiments are performed inside a computer, to obtain typical behaviour, or even outlier behaviour. One of the important problems at this time is to make these simulation systems robust enough, in order to be able to draw scientific economic conclusions from them. Especially

It is expected that one of the next steps in ACE is to design economic software agents with these interdisciplinary backgrounds, from psychology to anthropology.

within computer science, but also in economics, this is one of the current focusing areas of research [1], [2]. This area is better known as agent-based computational economics, or ACE.

Besides simulating real markets, CI techniques are also used in a similar way in the design process of multi-agent systems. Such systems, consisting of multiple software agents (autonomous software modules that coordinate with each other), often have some mechanism for coordination between the agents in the form of an economic game, like auctions, negotiation, or voting. As mentioned above, at the moment that we consider repeated games, many theories do not fully hold any more, and simulation comes into consideration. Especially, when the agents are not pre-designed but are non-cooperative and can be designed and instructed by different parties, the aggregate behaviour of a system difficult to predict. Since agents are considered to be (potentially) adaptive and learning, such learning capacities should be built-in in the simulated agent system. In this way, the aggregate behaviour of such software agent systems can be studied and experimented with. An example is online advertisement, i.e., the design of markets for software agents that bid for displaying an advertisement on a web site. The validation of such a system can be done by implementing adaptive software agents with EAs or NNs, and drawing conclusions from numerous computer experiments [6].

Economic Policy Design: An Economic Perspective

In the early years of work in agent-based computational economics, the focus was almost entirely on descriptive issues of economic markets, recent years have seen a considerable amount of normative work in different areas of market design and economic policy analysis. The main agenda of such normative work is to examine how different types of economic environments and protocols influence the aggregate economic outcome if individual behavior is adaptive and in general represented by some CI technique. An indication of the trend towards normative analysis is the fact that two special issues of economic journals dedicated to agent-based economic policy design are published in 2008 ([17], [30]) and that large international projects on agent-based economic policy analysis, where computer scientists cooperate with economists, are on their way (see [16]). Contributions in active areas of research like market design, in particular the design of electricity markets (e.g., [8], [34]), labor markets (e.g., [33]) or auctions (e.g., [35]), the design of innovation policy (e.g., [31], [18]) or the design of agricultural policy (e.g., [24]) have demonstrated that agent-based models can address relevant economic policy issues that are unattainable for analyses based on standard economic models. Simultaneously, in computer science, this "reverse" field of adaptive mechanism design is studied more and more (e.g., [35]). In this case, mechanisms can be developed by evolving different mechanisms with EAs, while the evaluation of mechanisms is done by having adaptive agents "play" in the mechanisms. On the other hand, the explicit consideration of the heterogeneity and bounded rationality of interacting agents may also lead to new insights into policy issues that have been well explored in the economic literature like the effect of a Tobin tax [32] or the intertemporal design of monetary policy [4], [23].

In spite of this fruitful recent work, ACE models are still far from being considered as a standard tool for economic policy analysis. Besides typical inertia of the economic profession to pick up new methods, a number of critical aspects of the ACE approach might be blamed for that. Important issues in that respect are empirical model validation and robustness checks (see above) of the derived results. The large flexibility with respect to the setup of agent-based models and the almost unrestricted number of potential model parameters give many degrees of freedom to the modeler and make it difficult to restrict the ranges of model parameters based on empirical data. This poses serious challenges to the use of ACE models for the evaluation and design of economic policy measures. For example, to what extent is the dynamics of the economic system in the simulation model indeed a good representation of the impact it would have in reality? In recent years, different proposals have been made on how to deal with this problem, and although the issue is far from being solved, the emerging literature in this field is starting to give ACE researchers some systematic guidelines about how to deal with empirical validation issues. We refer to [19] and [44] for an extensive discussion of empirical validation of agent-based models.

Competing Scientists

Interestingly, competitions exist where researchers can actually design and compete adaptive strategies for bidding and trading. An example is the Trading Agent Competition (TAC), where agents represent travel agents that have to get good bundles of hotel rooms, flight tickets, and entertainment tickets for specific periods, in different types of markets and economic games. Although several researchers use more traditional techniques from operations research or game theory, more and more researchers develop either adaptive strategies by CI techniques or even simulate the entire markets to obtain good strategies [42], [43], [48]. Recently, also the "inverse" competition on adaptive mechanism design started (CAT) [45].

In terms of repeated social dilemma games, there have been competitions of strategies for IPD games under different conditions [29], [47].

Conclusions

Developing CI techniques for economic games and policies is a very promising and fast-growing field. Several interesting multi-disciplinary subfields exist, which require researchers of various disciplines to collaborate with each other and contribute to the advances of knowledge in this emerging new field.

Obviously, in both computer science and economics, there are still many open questions and challenges, ranging from robustness issues to co-learning aspects, and from economic modeling, validation, and interpretation to large-scale simulation of complex adaptive systems. It is essential that such multi-disciplinary research challenges are tackled in a true multidisciplinary approach by both computer scientists and economists. We hope this short article will encourage more researchers and practitioners to join the exciting research in CI in economics [46].

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