An agent-based taxonomy of adaptation in computational economics
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ABSTRACT: Adaptation, learning and evolution play an important role for the analysis of financial markets in agent-based computational economics. Studying agent adaptation in financial markets can be very informative for understanding the internal workings of the market processes. Conversely, studying (financial) markets modeled as systems of a large number of learning and adapting agents can provide valuable understanding of adaptation and the design of adaptive systems. We propose to investigate this symbiotic relation between agent-based computational economics and adaptive systems by using smart adaptive systems. A starting point for the investigation of smart adaptive agents in computational economics must be the investigation of a framework for adaptation in agent-based systems. A hierarchical taxonomy of adaptation in agent-based systems for computational economics is proposed in this paper. The classification proposed introduces a hierarchy of adaptation schemes, where each level corresponds to the modification of specific components of a generic agent.

KEYWORDS: Intelligent agents, computational economics, adaptation, financial markets, agent-based economics, multi-agent systems.

1 INTRODUCTION

In recent years, agent-based approach to economical and financial analysis has grown into an important research field for developing an understanding of complex patterns and phenomena that are observed in economic systems. This field is now generally known as agent-based computational economics, which models economies as evolving systems of autonomous interacting agents. It studies the properties of complex systems through numerical analysis and simulation with a large number of interacting components that learn, evolve and adapt. Agent-based analysis has successfully been used to study how observed patterns and regularity arise in various areas such as transaction cost economics and financial markets. Another advantage of agent-based computational economics is that the paradigm can be used to make repeated and controlled experiments to collect empirical data in a way that is much more cost-effective than using real laboratories.

Adaptation, learning and evolution play an important role for the analysis of financial markets in agent-based computational economics. This is due to the unstructured and dynamic nature of the agents’ environment in complex systems such as the financial markets. Indeed, it has been observed that the complex price patterns such as volatility clustering, fat tails and speculative bubbles that are encountered in financial markets can be explained by the interaction of heterogeneous adaptive agents. Therefore, studying agent adaptation in financial markets can be very informative for understanding the internal workings of the market processes. Conversely, studying (financial) markets modeled as systems where a large number of agents learn and adapt to the changes in the environment can provide valuable understanding of adaptation and the design of adaptive systems. We propose to investigate this symbiotic relation between agent-based computational economics and adaptive systems by using smart adaptive systems. A starting point for the investigation of smart adaptive agents in computational economics must be the investigation of a framework for adaptation in agent-based systems. This paper considers adaptation in agent-based systems from a systems theoretic point of view and proposes a hierarchical taxonomy of adaptation in agent-based systems for computational economics. Adaptive systems have already been studied at a conceptual level within the fields of systems theory and organization theory. Various classifications for adaptation have also been proposed in the literature. In this paper, the most salient results are considered for agent-based systems, and a classification of adaptation is proposed that agrees closely with the specific characteristics of the agent-based systems. The classification proposed introduces a hierarchy of adaptation schemes, and at each level in the hierarchy corresponds to the modification of specific components of a generic agent. At each level in the hierarchy, the adaptation can be structural as well as functional. Further, it is shown that
different adaptation mechanisms such as imitation, reaction, learning and evolution can be employed at each level of the hierarchy.

The outline of the paper is as follows. Section 2 gives a brief overview of agent-based computational economics and the types of research questions that are addressed with this methodology. The role of adaptation in these studies is also discussed. Section 3 considers agent-based systems and different types of agents in terms of a generic architecture. A system theoretic overview of adaptation is discussed in Section 4, mainly by considering previous results from the literature. A classification of adaptation in agent-based systems is proposed in Section 5 based on the overview from Section 4. Different adaptation mechanisms are considered in Section 6, together with examples regarding how they manifest themselves in financial markets. Finally, the conclusions are given in Section 7.

2 ADAPTATION IN COMPUTATIONAL ECONOMICS

Economical systems such as financial markets can be considered as multiple auction environments, where the market mechanisms and the interaction amongst various market parties help compute a price for the traded asset. Recent research has focused on the computational properties of the markets themselves, by considering what computations various types of markets make, and how the markets can be designed to perform specified computations such as the minimum asset price (Shoham and Tennenholz, 2001). Hence, markets can be viewed as elaborate machinery that performs computation (e.g. price determination) in a distributed manner. Agent-based computational economics studies such economical systems by modeling them as evolving systems of autonomous, interacting agents (Tesfatsion, 2001). There is a wide recent literature focusing on this area (LeBaron, Arthur and Palmer, 1999; Lettau, 1997; Shoham and Tennenholz, 1997; Noriega and Sierra, 1999). A number of computational simulation laboratories have also been developed for agent-based economics (Arthur, Holland, LeBaron, Palmer and Tayler, 1997; Loistl and Vetter, 1997).

Adaptation, learning and evolution play an important role in the working of economical systems such as financial markets. Financial theory, for example, predicts that the markets are efficient (Fama, 1970), but anomalies are known to exist (De Bondt and Thaler, 1987). Various patterns in financial markets, such as volatility clustering, fat tails and speculative bubbles have been related to the interaction of heterogeneous, adaptive agents (Hommes, 2001). Agent-based computational economics has focused mainly on evolutionary adaptation of agents in large communities (see, e.g. (Lettau, 1997; LeBaron, Arthur and Palmer, 1999). In many studies regarding agent-based computational economics, the agents learn winning strategies through evolution (LeBaron, Arthur and Palmer, 1999). For example, the traders in a market may possess different trading rules and ways of updating these rules. It is assumed that unsuccessful traders will lose money, and hence prove to be ‘less fit to survive’ and so will be replaced by traders who use more successful trading rules. This analysis, however, fails to acknowledge the dynamics of the system, and the effects of different adaptation strategies and mechanisms that the agents can employ. Therefore, a more general consideration of adaptation in agent-based systems is useful to obtain a full understanding of the possible adaptive properties of the agents and their influence on the overall behavior of financial markets. Individual learning and social behavior of agents are expected to have a large impact on the emergence of various effects like self-organization, emergent patterns and the formation of belief systems. In order to study these more complicated forms of interaction, the agents themselves must possess a rich cognitive structure, be more sophisticated and have a large degree of autonomy and “intelligence.” It is thus worth to study the interaction of agents in societies of intelligent agents, leading to the investigation of smart adaptive agents.

3 AGENT-BASED SYSTEMS

An agent-based system involves one or more agents operating to meet their design objectives. Russell and Norvig define an agent very broadly as anything that can be viewed as perceiving its environment (through sensors) and acting upon that environment (through effectors) (Russell and Norvig, 1995). The definition of “environment” is given in the next section. For the time being, assume that the agent’s environment can be characterized as a set of environment states \( S = \{ s_1, s_2, \ldots \} \) that the agent can influence only partially. The influence of the agent is effected through a set \( A = \{ a_1, a_2, \ldots \} \) of actions that the agent can perform. The agent can then be viewed as a function \( \text{action} : S \rightarrow A \) that maps environment states to actions (Wooldridge, 1999). The (non-deterministic) behavior of the environment can also be modeled as a function \( \text{env} : S \times A \rightarrow \mathcal{P}(S) \), which maps the current environment state and the action of the agent into a set of environment states. The range of the \( \text{env} \) function is always a singleton in case the environment is deterministic. Note that this definition of an agent completely parallels the definition of a decision maker in a decision environment. Hence, one could argue that this is a decision-theoretic approach to agents.

Typically, the agents observe the environment states only partially. Therefore, the agent’s actions will depend only on a set \( P \) of percepts, which consists of a subset of the environment states and quantities that can be derived from the
environment states. It is part of the agent’s design to determine which percepts it can map from the available signals. In the formalism of this section, this mapping can be represented as a function \( \text{see} : S \rightarrow P \). The agent’s decision making mechanism now maps (sequences of) percepts to the actions of the agent. Let \( f \) denote this mapping. Then we have \( f(P, \Theta) : P \rightarrow A \), where \( \Theta \) denotes a set of parameters with which the mapping \( f \) can be parameterized. An agent’s function can now be specified by defining its set \( P \) of percepts, set \( A \) of actions and the mapping \( f(P, \Theta) \) from the percepts to the actions as shown in Fig. 1. It is assumed for simplicity that the specification of \( P \) also implies the specification of the function \( \text{see} \). Hence, the definition of this function is not considered explicitly in this paper. However, it could be included if a more detailed analysis is required.

There are two important points for the specification of the mapping \( f \). First, there is the set \( I \) of intended outcomes or intentions of the agent. Second, there is the set \( G \) of the goals that the agent is pursuing. The goals are often derived from the intentions of the agent. For instance, if the intention of an agent is to park a car, then one of the goals might be “to avoid a collision.” Note that the constraints that an agents wants to satisfy can be formulated within the set \( G \), while the physical constraints are implicitly present in the mapping \( \text{see} \). An agent must take both its intentions and its goals into account. The sets \( f \) and \( G \) can be defined explicitly as in the belief-desire-intention (BDI) architecture for intelligent agents (Wooldridge, 1999). In other architectures, \( I \) and \( G \) may be defined only implicitly through specific choices for the mapping \( f \), such as in the case of agents with the subsumption architecture (Brooks, 1986).

An agent’s adaptive properties can now be described in terms of modifications to any of the elements described in this section. Such an approach is taken in Section 5.

4 ADAPTIVE SYSTEMS

Various researchers have investigated adaptation in different contexts from a system theoretic point of view (Ashby, 1954; Beer, 1995; Zadeh, 1963). Organization theory has also considered adaptation, and several taxonomies for classifying adaptive systems have been proposed (Sagasti, 1970; Smet, 1998). In systems theory, a system is defined as “an entity which consists of two or more elements and a non-empty set of relations amongst the elements” (Sagasti, 1970). Note that this is a very general definition, which does not involve aims, functions or purposes. The set of elements in a system can be divided (somewhat arbitrarily) into two disjoint subsets, one of which is called the “environment” and the other is called the “object.” In agent-based systems, the object is an agent, while the rest of the system constitutes the environment. In multi-agent systems, the agents that are not of direct concern to the researcher (not studied directly) are thus part of the environment. Sagasti defines these two subsets as follows (Sagasti, 1970). The environment is a subset of the elements of a system such that the relationships amongst the elements of the subset are of no direct concern to the researcher. Similarly, the object is a subset of the elements of a system such that the relationships amongst the elements of the subset are of direct concern to the researcher. Clearly, the object in an agent-based system is the agent itself.

Systems adapt by modifying their elements or the relations between the elements as a result of stimuli from different elements of the system. In adaptation, this modification is not random, but is ultimately linked to the satisfaction of an external criterion such as keeping certain system parameters within pre-defined values (Ashby, 1954). Depending on the location of the stimuli and the location of the changes triggered by the stimuli, adaptation can be considered along two dimensions (Sagasti, 1970). The adaptation is said to be internal if it takes place in response to stimuli occurring in the elements of the object. It is said to be external if it occurs in response to the stimuli in the environment. If the response of the system that displays adaptation is directed towards modifying its object, the adaptation is said to be Darwinian. The adaptation is said to be Singerian whenever the system’s response is directed toward modifying its environment. One can now distinguish between four types of adaptation depending on the position along the two dimensions.

- **Darwinian external adaptation.** Stimulus is located in the environment and the system responds by modifying its object. This is the most common type of adaptation considered in the literature. The object tries to accommodate to the changes in the environment. An adaptive trading system that modifies the trading rules’ parameters as the environment changes is an example of this type of adaptation.

- **Darwinian internal adaptation.** Stimulus is located within the object. The system responds by modifying its...
object. An example of this type of adaptation is encountered when the attitude to risk of a trader changes as s/he ages.

- **Singerian external adaptation.** The stimulus for adaptation is in the environment, and it reacts by modifying the environment. Conventional control systems and reactive systems fall under this category. A major supplier of a product, for example, may react to the changes in its market share (related to the market size of other actors in the environment) by taking actions in order to counteract the loss in the market share.

- **Singerian internal adaptation.** The adaptation is triggered by stimuli in the object and the system reacts by modifying its environment. An example of Singerian internal adaptation is a specialized trader that changes the market in operates in because of personal preferences (e.g. someone who switches trading from NASDAQ to NYSE).

An implication of this classification is that the agents need not self-modify for the agent-based system to be adaptive: they can also modify only their environment. However, Darwinian adaptation is clearly more important for the design of intelligent, adaptive and learning agents. In addition to the classification in terms of the location of the stimulus and response, the adaptive property of a system can be characterized according to whether the adaptation is structural or functional. A system that produces a class of entities displays structural adaptation if one or more modifications of the system’s elements or of the relations between the elements changes only the level of efficiency of the production of the entities. The entities produced remain the same. For example, a trader that adjusts its rate of trading to the volatility in the market shows structural adaptation. A system displays functional adaptation if one or more modifications of the system’s elements or of the relations between the elements changes the entities produced. For example, a shopping agent that changes its intention of buying a product into buying another product because the former is not available in time displays functional adaptation.

It should be noted that the distinction between structural and functional adaptation can also be made for the elements of a system. An element of a system shows structural adaptation if it tries to maintain its function for other elements. It displays functional adaptation when its function in relation to other elements changes. When an agent is considered in terms of its elements described in Section 3, i.e. percepts, actions, the mapping between the two, the goals and the intentions, structural and functional adaptation can be distinguished for each of the elements. This consideration leads to an agent-based classification of adaptation as explained in Section 5.

5 **TAXONOMY OF ADAPTATION IN AGENTS**

Adaptation in agent-based systems is usually considered in terms of learning or evolution of agents. In general, adaptation denotes all changes to a system (agent and its environment) so that it becomes suitable for a given situation or purpose (Weiß, 1995). However, multi-agent literature has largely ignored this broad definition of adaptation, and it has concentrated its efforts on the incorporation of machine learning algorithms in the agents’ behavior so that the agents can accommodate to the changes in the environment in order to achieve their goals (Weiß and Sen, 1995). Influence of the agent on its environment receives less attention in this approach.

Agents in agent-based systems are typically goal-directed. Depending on the level of complexity for expressing and organizing the goal-directed behavior, the adaptation in agent-based systems can also be classified in a hierarchical manner. Based on the classification of adaptive systems from Section 4, this section proposes a hierarchical taxonomy of adaptation in agent-based systems, where the adaptive properties of the agents become stronger and more complex at each level of the hierarchy.

Recall that the generic agent model from Section 3 has five components, namely the set of percepts \(P\), the set of actions \(A\), the mapping \(f(P, \theta)\) between the percepts and the actions, the set of goals \(G\) and the set of intentions \(I\). The last two elements, \(G\) and \(I\) can be explicit in the agent’s design, or they can be implicit. The classification scheme proposed below also gives the mapping from each level of classification to the elements of the agent that need to be modified. Clearly, the emphasis here is on Darwinian adaptation, since the most expressive results are obtained when the agents themselves are modified.

We distinguish four levels of adaptation in agent-based systems.

- **Weak adaptation.** In this type of adaptation, the agent determines its output from its percepts according to a static mapping \(f(P)\). This mapping (along with \(P\) and \(A\)) is determined at design time, and it remains fixed during the agent’s lifetime. The agent can modify its environment, however, in different ways, depending on its percepts. Therefore, this level of adaptation is Singerian only, and the agent itself is not adaptive since it is not modified. A technical trader with fixed trading rules can be regarded as an agent operating at this level (fixed actions influence price formation in the market — the environment).
Table 1: Adaptation in agents.

<table>
<thead>
<tr>
<th>adaptation type</th>
<th>structural modification</th>
<th>functional modification</th>
</tr>
</thead>
<tbody>
<tr>
<td>semi-weak</td>
<td>parameters</td>
<td>function classes</td>
</tr>
<tr>
<td>semi-strong</td>
<td>goals</td>
<td>percepts</td>
</tr>
<tr>
<td>strong</td>
<td>goal function parameters</td>
<td>goal function classes</td>
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<td></td>
<td>intentions</td>
<td>actions</td>
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<td>goal ordering</td>
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<td></td>
<td>strategies</td>
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- **Semi-weak adaptation.** At this level, the mapping from the percepts to the actions can be modified. Either the function is parameterized to \( f(P, \Theta) \), and the parameters are adapted, or the class of functions that \( f \) belongs to is changed (e.g. from a linear mapping to a quadratic mapping). The sets \( P \) and \( A \) are assumed to be fixed. An agent whose decision mechanism is a neural network operates at this level during training or on-line learning.

- **Semi-strong adaptation.** At this level, an agent can modify its goals. A goal is generally represented by a goal function that assigns a utility to various states of the environment and the agent. The goals can be modified by modifying the goal functions (either through their parameters or through their function classes). An interesting modification of the goals is achieved by changing the set \( P \) of percepts. Since the agent observes the states of the system through its percepts, changing the percepts will automatically lead to a functional change in the goals of the system (the agent can be assumed to have a different representation of the world). A financial agent that modifies its expected returns as the volatility (risk) of the asset prices changes displays semi-strong adaptation.

- **Strong adaptation.** The agents operating at this level can modify their intentions and manage the strategies for achieving their design goals. Modifications to the priority of the goals imply changed intentions. At this level, the agent may also change its set \( A \) of actions. This changes the functionality of the agent completely and corresponds to the strongest form of adaptive systems, namely to *functionally adaptive systems* of Sagasti (Sagasti, 1970). Functional (strong) adaptation is often seen in complex systems. For example, when a trader starts leasing its assets in addition to buying and selling, we observe functional adaptation.

Note that the classification proposed is incremental, i.e. an agent that displays semi-weak adaptation can also display weak adaptation, an agent that displays strong adaptation can also display all other types of adaptation, etc. Furthermore, the classification is done purely from the point of view of the adaptive properties of the agents themselves (as opposed to the adaptive properties of the agent-environment pair). It does not imply that complex behavior can only be achieved at stronger forms of adaptation. In fact, agents with a subsumption architecture are weak adaptive, but they can still solve complex problems cooperatively (Steels, 1990). However, semi-weak, semi-strong and strong forms of adaptation are more relevant for adaptive agents, and hence we concentrate only on these forms of adaptation in the remainder of this paper.

An agent’s adaptation at different levels of hierarchy can be structural or functional. In semi-weak adaptation, the modification of the parameters \( \Theta \) is structural adaptation. The modification of the class of functions is functional adaptation (for that element). Similarly, the modification of the goals in semi-strong adaptation can be structural through the modification of the function parameters or functional through the modification of the function classes. Modification of the percepts also corresponds to functional adaptation. Finally, the modification of the actions in strong adaptation corresponds to functional adaptation of the agent. The proposed classification of adaptation in agents is summarized in Table 1.

### 6 MECHANISMS FOR ADAPTATION

We have seen in Section 5 that agents can display adaptive behavior by modifying any of their components. An important question is, how this modification can be performed on the different levels of adaptations we introduced. Without going into the details of criteria for evaluating the effects of change, we give in this section a brief list of various mechanisms with which agent-based systems can adapt. Imitation, reaction, reactive learning, generative learning and evolution are the adaptation strategies which can be considered by agents in order to achieve adaptive behavior (Smet, 1998; Droste, 1999).

- **Imitation.** One way to achieve adaptation is to simply copy observed data, actions or solutions. The mapping from the percepts to the actions can be obtained by copying the action of an observed agent. Agents operating on
different levels of adaptation can copy percepts, actions, goals or intentions of other agents. Of course it must be possible to observe other agent’s components and actions. In financial markets, traders may mimic the actions of other traders, for example, who are known to be successful.

- **Reaction.** Reactions are direct responses to particular events or changes. They can be typically expressed in the form of if-then rules or in the form of mathematical formulas. For example, agents providing semi-weak adaptation can use the mechanism of reaction for modifying their parameterized function. A trader, for example, that sells an asset when its price falls below a certain value demonstrates adaptation by reaction.

- **Reactive learning.** Past experience plays an important role in the process of reactive learning. Agents that provide reactive learning coherently use received feedbacks when making future decisions. Reactive learning is a technique that can be used for modifying (based on experience) the parameters or the functions at the level of semi-weak adaptation. Goals in semi-strong adaptation or strategies and actions at the strong-adaptation level can also be modified through reactive learning. Technical traders that update their trading models based on past trading data learn reactively.

- **Generative learning.** Generative learning refers to a kind of innovative learning, to an anticipatory modification of the components. This type of learning is more goal-oriented. Anticipating new goals, intentions or actions at the two highest levels of agent based adaptation implies generative learning. A financial institute that develops a new financial product based on an anticipation of market developments can be said to show generative learning.

- **Evolution.** Evolutionary adaptation modifies various components of the agent gradually during successive generations. It can be used for semi-weak, semi-strong and strong adaptation provided there is a mechanism to inherit properties across generations for the adaptation of species (phylogenesis). In a financial market, for example, trading rules that lead to a loss of money consistently are selected away by evolutionary mechanisms (e.g. the trader that uses them goes bankrupt).

7 CONCLUSIONS

Adaptation of agents has a central role in agent-based economical analysis. Studying agent adaptation in financial markets can be very informative for understanding the internal workings of the market processes. Conversely, studying (financial) markets modeled as systems of a large number of learning and adapting agents can provide valuable understanding of adaptation and the design of adaptive systems. We propose to investigate this symbiotic relation between agent-based computational economics and adaptive systems by using smart adaptive agents. Agents often exhibit goal-directed behavior. In order to survive and achieve their intended results, agents operating in a highly dynamic environment are required to be adaptive. The adaptive behavior of agents can be obtained by modifying any of their generic components. This paper has shown that the modification of the generic components of an agent can be organized in a hierarchical manner leading to a hierarchical classification of adaptation. A hierarchical taxonomy of possible adaptation types in agent-based systems is introduced for this purpose. In the future, we expect our taxonomy to be useful for analyzing the behavior of financial markets by considering the different possibilities for adaptation in a systematic way.

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