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Detecting change and dealing with uncertainty in imperfect evolutionary environments

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ABSTRACT

Imperfection of information is a part of our daily life; however, it is usually ignored in learning based on evolutionary approaches. In this paper we develop an Imperfect Evolutionary System that provides an uncertain and chaotic imperfect environment that presents new challenges to its habitants. We then propose an intelligent methodology which is capable of learning in such environments. Detecting changes and adapting to the new environment is crucial to exploring the search space and exploiting any new opportunities that may arise. To deal with these uncertain and challenging environments, we propose a novel change detection strategy based on a Particle Swarm Optimization system which is hybridized with an Artificial Neural Network. This approach maintains a balance between exploitation and exploration during the search process. A comparison of approaches using different Particle Swarm Optimization algorithms show that the ability of our learning approach to detect changes and adapt as per the new demands of the environment is high.

1. Introduction

An individual as a system shows intelligence with its actions, i.e. an intelligent individual reacts according to its surrounding and needs. The behavior of an intelligent individual is expected to be in coherence with the current situation which the individual is experiencing. The individual should cater for the changes in its environment and objective(s) enabling itself to make the appropriate decisions under perceptual and computational self-limitations [38]. Ideally, an intelligent entity should be capable of detecting new information which becomes available at any time, extracting the relevant knowledge, learning and reacting accordingly without the need of any third party intervention, thereby forming a dynamic relationship with its surroundings. Our work deals with this relationship of an intelligent entity with its surrounding environment. We argue that this relationship has been ignored in the past and our experimentation will show how this ignorance affects the abilities of learning agents.

In this paper we deal with dynamic environments of *imperfect* information, i.e. the set of information changes over time. The information available in the environment is incomplete because new information is constantly added to it or previous information is removed from it. This information can be anything from the availability of new input parameters, changes in

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the objective(s) of the agents or changes in the rules of the environment. The notion of imperfection in evolutionary environments, which will be referred to as Imperfect Evolutionary Systems (IES) from this point forward, was presented by Kendall and Su [25]. IESs are uncertain and chaotic (where the changes can occur abruptly at any time) dynamic environments which provide a variety of challenges to the learning individuals residing in them. In simple words, in a dynamic environment of perfect information, we know what we do not know, whereas in an IES we do not know, what we do not know.

Learning in an IES is limited by the information available, any addition to this information opens up new avenues of learning and acquiring new skills become possible. Such imperfection of information is commonly found in real world problems. A human player may play checkers and then look at a game of chess and decide to learn that game. The same player may focus on other games or may learn a different task altogether. Investors in a stock market may change their strategies based on new information that was not previously available to them. This new information maybe a change in the known indicators that contribute to stock prices or it may add a new indicator previously unknown. The same investor may then leave for a racing track and decide to make bets on a racing horse. These two problems would require analysis of a completely different set of parameters. This ability to deal with imperfection also allows humans to deal with new problems or challenges in our daily life and enables us to detect irrational or unnatural behavior in known scenarios. Humans are able to detect when another player is cheating in a game but evolutionary strategies have had limited success in detecting such behavior.

We argue that the problem facing an intelligent entity is not only to excel in solving a particular problem but also the ability to deal with any problem without any *a priori* information. Due to its uncertain and dynamic nature, an IES presents new challenges to its habitants. These changes in the environment require its habitants to adapt according to the challenges and modify behavior without the need to rely on any human assistance.

Traditional learning approaches fail to embrace the incomplete nature of an IES. We believe, this failure is mostly due to ignorance of the learning strategy to its surroundings. They assume the environment to be perfect and complete; therefore addition of new information is ignored in the evolutionary process. Another weakness of traditional approaches lies in handling detection of changes. These techniques either rely on human intervention to provide information about the changes or change detection is mostly done by reevaluating currently known solutions to see if their fitness values have changed or not. Results of our experiments will show that this approach to detecting change limits the ability of a learning algorithm to perform in noisy and imperfect environments. Furthermore, a simple re-initialization of agents would not be enough to cater for the updated information added to or removed from the situation. Re-initialization of best strategies also means to abandon all learning done till that point and all computational cost till that point is wasted.

In our work we present a learning algorithm that overcomes all these problems. We propose learning to be a continuous process, broken learning into three abstract and simplified sub-processes. Our learning strategy allows individuals to build a dynamic relationship with their surroundings based on the information available to them. Whenever this information changes, these individuals assess their performance and effectiveness of their strategies. If new information is found to be relevant to an improvement in chances of survival then this information is added to knowledge pool otherwise it is discarded.

Our results will show that this learning approach performs well in both perfect and imperfect environments. However, our primary focus in this work has been to create intelligence that is capable of dealing with the incompleteness of any environment. Our learning approach is able to handle abrupt uncertainties which are inherent in an IES. We will show how traditional learning approaches fail to meet the needs of an imperfect world. These approaches either ignore the availability of new information or rely on humans to provide explicit information about the change.

Since learning in such an environment is an ongoing process, it requires a learning approach that is continuous in nature. In this paper, we present such a learning approach that is able to seek its objectives in an imperfect world, detect changes occurring in the environment and adapt accordingly. Our learning approach allows agents to acquire new skills that help them survive the demands of their environment. These skills are acquired and updated by the agents themselves in an automated manner based solely on the information provided by the environment. No other information or guidance is provided to the learning algorithm. This allows agents to learn and adapt as per the requirements of their environment (these requirements change over time without any warning) and thus improve their chances of survival in an automated manner, mimicking the behavior of naturally intelligent individuals. Instead of optimizing a particular skill for a particular environment, we aim to develop an approach that allows agents to learn multiple objectives (or skills) on their own without any human guidance.

In order to test our hypothesis of continuity of learning in uncertain environments we developed an IES to perform our experimentation. This IES is modeled to handle uncertainty and imperfection of information and create new challenges for its inhabitants. It constitutes of different entities both learning and non-learning. We believe that the abstract nature of the environment would allow other researchers to add new entities and challenges to it. Fig. 1 presents a diagrammatic view of this IES at different time stages. E^T is the state of the Imperfect Evolutionary System at time T (represented by the large outer circle). E^T is defined by a set of information blocks. Any change in the environment will bring about a change in the search space with the consequence of no point being the optimal for all the different states of the environment. New information for inhabitants would present exploration opportunities (Fig. 1b), whereas removing previously available information would render evolved strategies to be obsolete (Fig. 1c). Hence we can define E^T in terms of the information available to its inhabitants as in Eq. (1).