A Dual-Mode Learning Mechanism Combining Knowledge-Education and Machine-Learning

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Abstract. From 1956, the definitions of learning according to Artificial Intelligence and Psychology to human mind/behavior are obviously different. Owing to the rapid development of the computing power, we have potential to enhance the learning mechanism of AI.

This work tries to discuss the learning process from the traditional AI learning models which are almost based on trial and error style. Furthermore, some relative literatures have pointed out that teaching-base education would increase the learning efficiency better than trial and error style. That is the reason we enhance the learning process to propose a dual-perspective learning mechanism, E&R-R XCS. As for XCS is a better accuracy model of AI, we have applied it as a basement and proposed to develop an intelligence-learning model. Finally, this work will give the inference discussion about the accuracy and accumulative performance of XCS, R-R XCS, and E&R-R XCS respectively, and the obvious summary would be concluded. That is, the proposed dual-learning mechanism has enhanced successfully.

Keywords: Artificial intelligence, Psychology, Trial and error, Teaching-base education, Intelligence-Learning.

1 Introduction

Traditionally, Artificial Intelligence, according to the definition of Computer Science, works as helpful machines to find solutions to complex problems in a more human-like fashion [1,2]. This generally involves adopted characteristics from human intelligence, and it applies them as algorithms in a computer friendly way. A more or less flexible or efficient approach can be taken depending on the requirements established, which influences how artificial the intelligent behavior appears. Those researches, for example: Neural Network, Fuzzy Approach, Genetic Algorithm, and so on, all focus on Soft Computing. Of course, XCS (Extend Classifier System) is also a hybrid approach with high performance to the accuracy and the rule evolution on the prediction application. However, up to now, the Artificial Intelligence Techniques based on Soft Computing have all involved the concept, trial and error method or stimulus-response

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method even the series of evolution approaches, such as [1,2] and [3], to construct their learning models. For this aspect, if possible, this example, a Chinese idiomatic phrase-"An Illusory Snake in a Goblet", is taken into consideration as an input-output pattern to training the learning model. The models are formed for sure. It is actually a wrong model trained by a bad experience. Besides, the parameters of those training models are exactly affected by the input dataset, especially the large difference of the training inputs and testing ones. Usually, in many researches it is chosen the high relation between the input and output datasets or given the strong assumption which is the inputs and outputs are relevant. Thus, a subjective black-box view and the tuning view are easily concluded [4].

The other sub-domain, Expert System, which's primary goal is to make expertise available to decision makers and technicians who need answers quickly. There is never enough expertise to go around -- certainly it is not always available at the right place in the right time. The same systems in-depth knowledge of specific subjects can assist supervisors and managers with situation assessment and long-range planning. These knowledge-based applications of artificial intelligence have enhanced productivity in business, science, engineering, and even the military. Although, the development of those expert systems is the view of anti-extreme to construct domain knowledge first but, for the reason, they are lack of the flexibility and the adaption. In fact, each new deployment of an expert system yields valuable data for what works in which context, thus fueling the AI research that provides even better applications.

Many researches, no matter Soft Computing techniques or Expert Systems try to consider into the human-like thinking way to make the simulation. But, from classic psychology, the human-mind researches are the researches to the human-behavior. Since Plato, Psychology is an unfathomable philosophy and those advanced AI researchers should concern this perfect development of Human Psychology, from simple to complex and from single factor to multiple ones. However, the traditional AI techniques are seldom focused on the high level of human-mind process and just paid attentions to the learning definition from the Empricalism Psychology. According to the development of Modern Psychology, the core of Psychology has been already transferred Empricalism-base into Information Process Theory of Human-Mind, and even Cognitive Psychology-base. As for the knowledge and the model construction, the teaching-base aspect has been involved as well to the learning process. Based on the aspect, this work tries to enhance the learning process of traditional AI techniques whose cognitive scotomas of learning definition, and it develops the novel learning model, involving the concept of Cognitive Psychology, which is utilized the high accuracy-prediction XCS [5] model as the construction basement.

2 Relative Survey

2.1 Information Process Theory

Among previous learning artificial intelligence techniques, such as neural network, or its hybrid methods, all the models are formed by trial and error learning way, the traditional definition of learning. However, to enhance the learning style, a cognitive learning, Information Process Theory, would be worth to take into consideration. According to the information-processing model of learning (see Fig. 1), there is a series of stages by which new information is learned (Gagne, 1985) [6]. Information is received by receptors (such as the eyes and ears), from which it is passed to the sensory register where all of it is held, but for only a few hundredths of a second. At this point of view, selective perception acts as a filter which causes some aspects of the information to be ignored and others to be attended to. For example, the ears (receptors) receive the sounds comprising "Pi equals 3.14," along with various other background sounds, and all those sounds are passed on to the sensory register in the brain. Then through the selective perception process, some of the information (hopefully the "Pi equals 3.14") is attended to the part.

That information which is attended to is transformed and passed on to short-term memory, which can only contain a few items of information at a time (depending on their complexity). For instance, if "Pi equals 3.14" is attended to, it is then passed on to short-term memory, where it might be said to "echo" for a few seconds, and the echoing can be prolonged through rehearsal." Items can persist in short-term memory for up to about 20 seconds without rehearsal, but with constant rehearsal they can be retained indefinitely.

Finally, the information may be passed on to long-term memory. This process is called encoding to memorize. For example, if appropriate encoding processes are exercised to link the "Pi equals 3.14" with prior knowledge, then the information is passed on to long-term memory. In the traditional model of human memory (Atkinson and Shiffrin, 1968 [7]; Waugh and D. A. Norman, 1968 [8]), immediate free recall yields items directly retrieved from a temporary short-term memory (STM) and items retrieved by retrieval cues from a more durable storage in long-term memory (LTM).

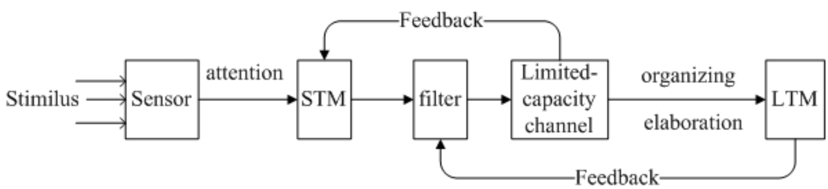

Fig. 1. Information Process Theory proposed by Gagne [9]

2.2 XCS

Most machine learning techniques are developed by information process theory. No matter partial application of IPT concept or applying the entire flow of IPT, they all simulated various operations of memory. For example, those neural network types are applications of neuroanatomy. According to that, it is necessary to define the neural structures of the brain simulated as memory. The others would be evolution computing types, such as GA, GP, and LCSs. Among them, LCSs has flexible outcome on rule generation which represents information about the structure of the world in the form of rules and messages on an internal message list, such as its STM or LTM, John Holland mentioned that. The system can be used as the message list to store information about (a) the current state of the world (response), and (b) about previous states (stimulus). From now on, LCS has the ability to store rule according to the input information.

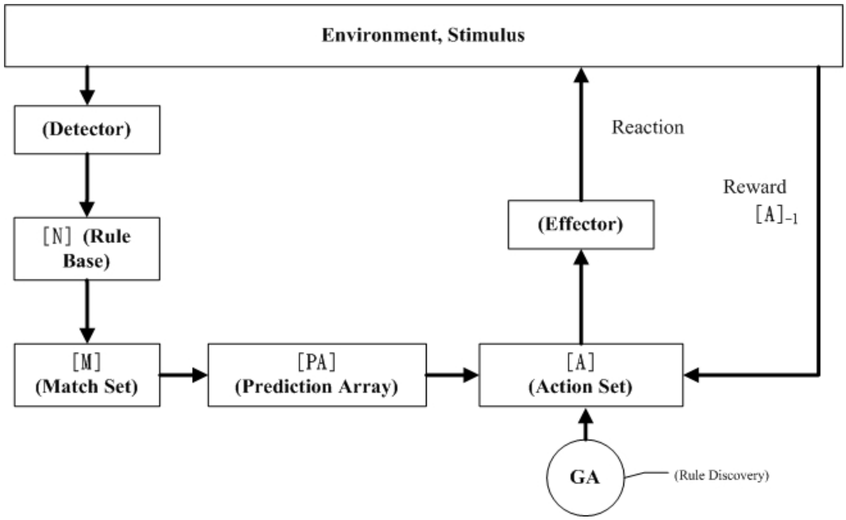

Fig. 2. XCS Procedure

However, Wilson's XCS [10] is a recently developed learning classifier system (LCS) that differs in several ways from more traditional LCSs. In XCS, classifier fitness is based on the accuracy of a classifier's pay-off prediction instead of the prediction itself. As a whole, the genetic algorithm (GA) takes place in the action sets instead of the population. XCS's fitness definition and GA locus together result in a strong tendency for the system to evolve accurate, maximally general classifiers that efficiently cover the state-action space of the problem and allow the system's 'knowledge" to be readily seen. As a result of these properties, XCS has been considered and focused to the kernel of the proposed model in this work.

XCS's detailed loop is shown in Fig. 2, and the current situation is first sensed and the detector received the input from the environment. Second, the match set [M] is formed from all classifiers [N] that match the situation. Third, the prediction array [PA] is formed based on the classifiers in the match set [M]. [PA] predicts for each possible action ai, the resulting pay-off. Based on [PA], one action is chosen for execution and the action set [A] is formed, which includes all classifiers of [M] that propose the chosen action. Next, the winning action is executed. Then the previous action set $[A]_{-1}$ (a previous action set) is modified by using the Q-learning-like payoff quantity P which is a combination of the previous reward p-1 and the largest action prediction in the prediction array [PA]. Moreover, the GA may be applied to $[A]_{-1}$. If a problem ends on the current, time-step (single-step problem or last step of a multi-step problem), [A] is modified according to the current reward, p, and the GA may be applied to [A]. The loop is executed as long as the termination criterion is not met. A termination criterion is a certain number of trials/inputs.

Finally, XCS's architecture is much neater development base on IPT than the previous models. However, XCS is not sufficient to represent IPT. The coming discussion would be given to its explanation.

2.3 Discussion

Using a computer as a metaphor for memory, the short-term phase is RAM (highly volatile and easily lost when some others else are entered), but long-term memory is such as a hard drive or diskette (the information is stored there even after the machine is turned off). This metaphor is especially helpful because a computer knows the address of each bit of information because of the manner information is entered. It is essential that information placed into a student's long-term memory be linked in a way that the student can retrieve it later. The teacher who should understand the relationship between memory and retrieval can lay out a lesson plan to assist the student in the process and enhance his learning.

As the pre-statement portrayed, while rehearsal is important to short-term memory, it can also be used to transfer information into long-term. Elaborating or making material memorable will also enhance the student's learning process. The effective teacher will elaborate and rehearse material so that the student can remember the information more easily. That is the reason the input material is high relevant to memorize to form valued-information, knowledge. However, it is important to note that most application AI models, even XCS model, have more trouble remembering/learning of what data they should remember/learn. Therefore, the entire learning procedure as the effective teacher help the memory process by introducing the student to various organizational techniques cannot come true.

3 Dual-Mode Learning Mechanism

3.1 Conceptual Framework

During the Middle Period (mid 1900s), Knowledge is just thought of as the transformation of sensory inputs into associated thought, and the realization that sensory inputs are transformed prior to storage. In the early twentieth century, Knowledge is still considered as a framework of stimulus and response (S-R). The profound breakthrough of this period is that by studying S-R, one can gain insight into the working of cognitive knowledge. This kind viewpoint of knowledge learning is largely based on narrow term of cognitive psychology, information processing theory. Furthermore, S-R of cognitive psychology research is historically analogous to the black box testing. Following these two aspects, this work applied the cognitive learning to modify the learning process of traditional soft techniques to increase the efficiency of forming knowledge storage. That is, combining the information process theory and knowledge learning to initial the concept of the dual learning mode framework is the purpose of this work, shown as Fig. 3. It contains two parts: Knowledge Education learning and Reinforcement-Rehearsal(R-R) learning.

3.2 Proposed Model (E-RR XCS)

R-R XCS model, a middle version to develop E-RR XCS, is also an enhanced version from XCS by adding a rehearsal mechanism. Owing to them both adapting GA as an

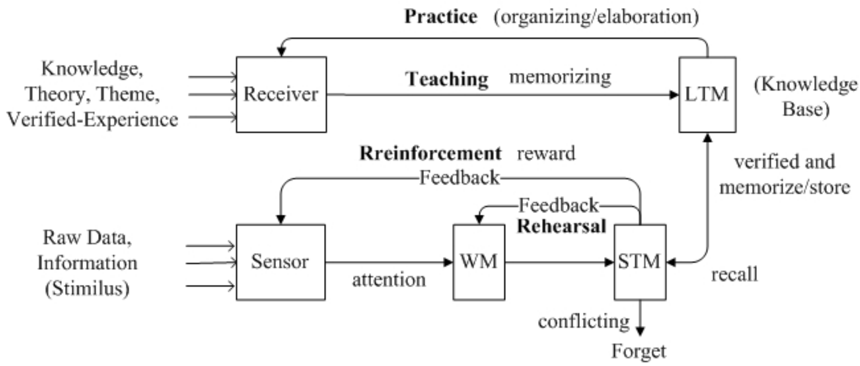

Fig. 3. Dual perspective learning process of Education and R-R mechanism

evolution methodology of classifiers and based on XCS, their working accuracy rate should be equivalent by the same training data and testing data. The leverage of R-R XCS to XCS deserves to be mentioned. The rational assumption is that R-R XCS has higher leverage to XCS. This reason originates from R-R XCS considering more value information automatically. But its performance would be decreased and its accuracy ratio might not be better than XCS [11].

Education & R-R XCS, an implantation of proposed learning concept, is to increase the accuracy ratio by concerning the education efficiency of learning. In Fig. 4, there are two starting points which is different from XCS. And E & R-R XCS involves R-R XCS discussed in pre-statement. Besides them, in the additional education learning part, discovered knowledge, verified theory, and defined theorem are all considered as input patterns to the mechanism. Those data should be valued and worthy to "teach" the model or the model should be learned/trained. Thus, we increase the practice route in the education part. (E & R-R XCS is a "model" not a student and the model is not necessary to be practiced for more than twice times.) For this, those input data would be easily memorized/ stored by the receiver and internalized to the knowledge rule base [N_1]. Population in knowledge rule base has higher weight or effectiveness than ones in experience rule base. Besides, the detector should consider more about the knowledge rule base [N_1] than about the experience rule base [N_2]. WM still stores the current situation in advance. Second, the match set [M] is formed from [N_1] or [N_2], which is either the knowledge rule base or experience rule base. The following steps are the same with R-R XCS ones. The difference is that the initial-picked population is more from knowledge rule base than experience one. In the mechanism, this kind population from knowledge rule base seems to be "principle". While the entire loop has finished, the new population should be generated from knowledge rule base to the experience one. Some experiences have possibility to produce from the real knowledge, if the knowledge really exists. Furthermore, while a rehearsal population from repeater to detector occurs, detector should verify the repeated population qualification that it may be transferred to receiver. The knowledge population, that is, does come not only from the outside environment but also from internal mechanism. The education knowledge should also be possible increased to the knowledge rule base [N_1], while the new knowledge or theory is discovered. As for the other detailed procedure same to XCS, they have already been detailed in pr-section.

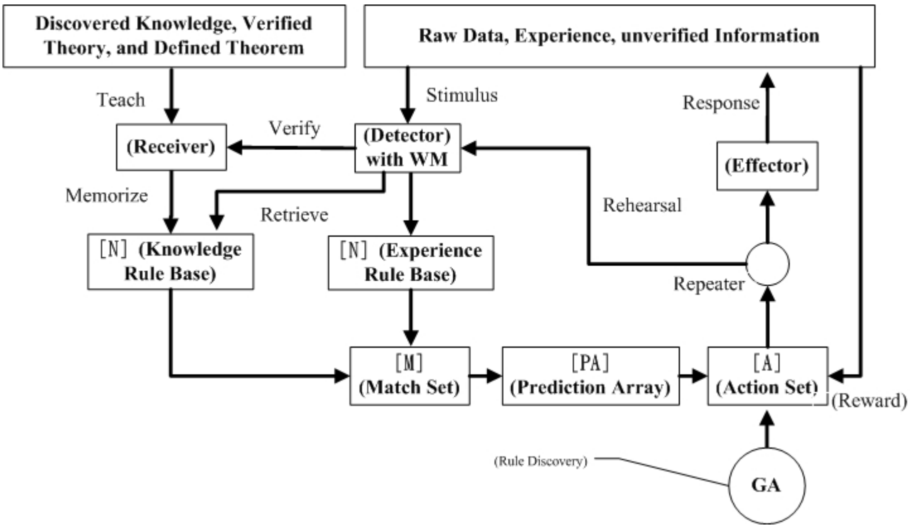

Fig. 4. E&R-R XCS Procedure

4 Inference Discussion

Actually, the case of adding new population from detector does not happen easily. E & R-R XCS exactly defines the stern discipline to the knowledge. In fact, the percentage of knowledge from detector to receiver ones is low. That is, the population in knowledge rule base should be maintained spotless correctness.

Following the descriptions, three inferences of these models are possibly deduced in this section. Their theoretical accuracy and accumulated performance would respectively be detailed as following. The x-axis, Time, in Fig. 5, 6, and 7 might means time, or times which is the operating times of the model. The y-axis is just the theoretical accuracy or accumulated performance.

4.1

In Fig. 5, γ is defined to the difference of the accuracy ratio of R-R XCS and XCS. λ is defined to the difference of the accuracy ratio of E&R-R XCS and XCS. It is sensible that $\lambda >> |\gamma| >= 0$. The reasonable explanation is R-R XCS with rehearsal learning focused on valuable information. When γ is approximate to zero, the two models are applied to the all original data. When $|\gamma|$ is large to zero, the two models are applied to identify the result for valuable information. As for λ, due to the education efficiency of learning, λ should be larger which means the accuracy ratio of E&R-R XCS is much better than XCS one.

4.2

In Fig. 6, μ is defined to the difference of the accumulative output of R-R XCS and XCS. It is sensible that $|\mu| >= 0$. The reasonable explanation is just R-R XCS with rehearsal learning focused on valuable information, but its accuracy rate is not absolutely better than XCS one. Indeed, the leverage effect of R-R XCS originates from it focused on more valuable information. If the output is correct and positive to the result, the accumulative output should be increased more. Contrary to the wrong one, the accumulative output should be decreased more as well.

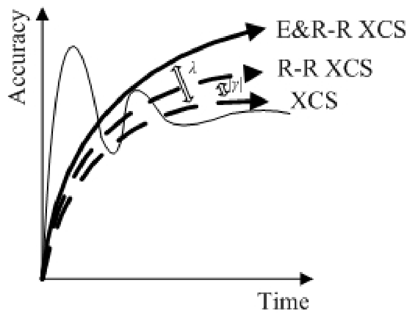

Fig. 5. Theoretical Accuracy of XCS, R-R XCS, and E&R-R XCS

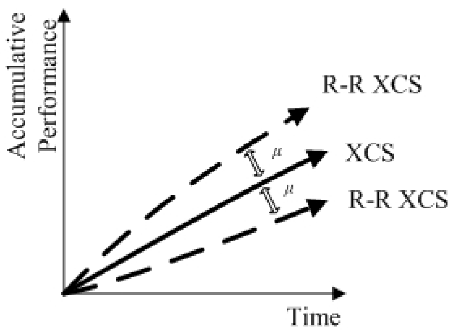

Fig. 6. Theoretical-Accumulative Performance of XCS and R-R XCS

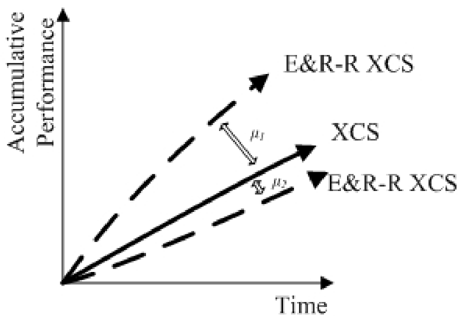

Fig. 7. Theoretical-Accumulative Performance of XCS and E&R-R XCS

4.3

In Fig. 7, μ_1 and μ_2 are defined to the difference of the accumulative output of E&R-R XCS and XCS. It is sensible that $|\mu_1| >> |\mu_2| >= 0$. The reasonable explanation is that E&R-R XCS has not only the ability with rehearsal learning focused on value information but also involves the education efficiency of learning. Therefore, its accuracy rate is absolutely better than XCS one. Indeed, E&R-R XCS still owns the leverage effect, which originates the same to R-R XCS. Owing to the accuracy ratio increased, the output is usually positive to the result, and the accumulative output should be increased much more.

In a word, the learning accuracy of the proposed E&R-R XCS is much better than XCS. R-R XCS comparing with XCS has the leverage effect to the accuracy and the accumulated performance at least.

5 Conclusion

Such as the description of this work motivation, much Knowledge discovery, Theory verification and Theorem definition are aggregated and not disregarded by this learning mechanism development. Also, they are all continually historical accumulated. That is still the reason that the civilization is enhanced, the culture is accumulated, and knowledge is transmitted.

Finally, this work successfully proposed an efficient dual-mode learning mechanism which combines the passive-learning (knowledge education) and the self-learning (machine learning) [12]. That is, the major contribution of this work is the proposed mechanism. Once, more accuracy ability of AI Techniques invented could be substituted for XCS and the mechanism performance would be more efficient.

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