Soft-Hard Memory for Cognitive Systems

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Abstract

We propose a novel memory infrastructure, called Soft-Hard Memory (SHM), and its corresponding learning scheme for cognitive learning systems. SHM is designed according to cognitive principles and based on the Soft-Hard Structure Theory. In SHM, memory is divided into soft-structure and hard-structure, which enables bootstrap and adaptive learning processes. It is intuitive, high-performance and easy to implement. Experiments in our robot project demonstrate its effectiveness.

Keywords: *Soft-Hard Structure, Memory, Learning, Cognitive System, Robot*

1 Introduction

People have been pursuing the object of "intelligent machine" for a very long time. Among all the intelligent features, learning is one of the most desirable. The most distinct feature of a learning system is that it can continuously learn from the environment, including its own performance and status, to improve itself. This feature is essential for life.

In recent years, machine learning (ML), a broad subfield of artificial intelligence, has developed rapidly. ML is concerned with techniques that enable computers to learn automatically. Researchers are making great efforts in developing such methods. Now, machine learning is receiving more and more attentions. And in the field of robot and computer vision, ML approaches are also widely applied. For example, Kazuhiko [1] uses Isomap [2], which is a non-linear dimensionality reduction (NLDR) technique in machine learning to discover low dimensional manifold, to learn the spatial-temporal structure of motion sequences in their robot system. In computer vision and graphics, clustering techniques have become a mainstream approach for graph-cut and image segmentation tasks [3].

Although machine learning has achieved a lot in developing practical intelligent methods to solve specific problems, its current learning paradigms are not suitable for human-like learning. Typical machine learning algorithms are based on strong hypotheses or models. What the machine learns is in fact parameters, while the underlying models can seldom change. Consequently, the data storage structure (memory) is also hierarchical. This framework is clearly not eligible for adaptive learning tasks. It is very hard to make right hypotheses. Even if the hypotheses are proper now, it may become unsuitable when the environment has changed. Another question is that, where did the models come from? There is little predefined knowledge, if any, in a human baby's brain, but he/she can still learn and grow to be an intelligent being. In fact, there have long been arguments that mainstream AI researches has deviated from the nature of intelligence. Specifically, in the field of ML, adaptiveness and the ability of bootstrap are the two missing features in most algorithms. By contrast, we call a learning method with these two properties cognitive learning.

Memory is thought to be the core of a cognitive system, and learning relies heavily on it. Before we can develop an evolving learning machine, a competent memory structure has to be built. Extensive investigations have been taken on human memory, but its actual mechanism is still unclear. Here we only focus on a satisfying engineering realization. In cognition and psychology, human memory is divided into short-term memory, working memory and long-term memory. Existing memory structures for cognitive systems are mainly based on this notion. For instance, Kazuhiko [1] uses the same memory configuration as described above, and has each part constructed specifically.

In this article, we design a memory infrastructure, called Soft-Hard Memory (SHM, pronounced as *shim*), to facilitate cognitive learning processes. In SHM, memory is divided into soft memory and its counterpart, hard memory. Basically, this memory scheme is also similar to the natural classification of human memory. However, it is designed from the perspective of evolution. Through the interaction between these two parts, the system can hopefully realize bootstrap and adaptiveness.

The rest of this article is organized as follows: In section 2 we analyze the human learning process and indicate necessary features of a cognitive learning system. Section 3 introduces the theory of Soft-Hard Structure and describes the Soft-Hard Memory in detail. In section 4, we introduce some preliminary experiments of this memory structure in our cognitive robot project. Conclusion is in section 5.

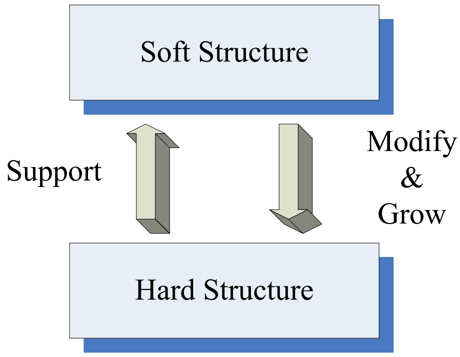

Figure 1: Soft-Hard Structure

2 Cognitive Learning

For any intelligent beings, either natural or artificial, adaptive learning is crucial to survive in changing environment. Current algorithms usually simplify the problems to estimation of parameters. However, unalterable models are obviously not suitable for adaptive learning, which is not just a process of accumulating and enhancing, it also involves the creation, reconstruction and oblivion of knowledge.

Moreover, human learning is a bootstrap process. That means we can learn infinite knowledge based on very few priors. From a micro-perspective, an infant can learn and grow to be an expert with little initial knowledge. And from a macro point of view, the accumulating of human knowledge is a phenomenal example. Neural science shows that this ability is mainly due to the structure of neural networks in human brains. From a engineering view, there must be some "grow point" in the system, where new models and concepts can be generated.

Adaptiveness and bootstrap ability are the two most importance features for cognitive learning. Clearly these two features are not feasible on a hierarchical memory structure since the number of layers is necessarily infinite. There must be some kind of feed back mechanism. Soft-Hard Structure [4] in generalized evolution theory provides such a solution.

3 Soft-Hard Memory

3.1 Soft-Hard Structure Theory

Creation of knowledge is the most difficult task in learning. Ashby [5] proposed Ultra Stable System as the simplest model for creative machines. In this system, status of the machine keeps changing randomly until the evaluation module finds a good result. Thus a creation is realized. Yet, this system is not feasible for complex tasks since it is computationally impossible for a large amount of variables.

In order to avoid the difficulty of computing, the system should not run in a totally random manner. To solve this problem, we can learn from evolution, which is the most spectacular process of creation in nature. Aberrance and selection is the core of Darwin's evolution theory. Zhao [4] proposed that soft-hard structure (SHS) is also a key for evolution to success.

According to SHS theory, an evolutionary system can be divided into two parts: soft structure and hard structure. Soft structure is the active part where creations and reconstructions occur. Hard structure is the static part which supports soft structure and subsistence of the system (Figure 1). The key idea of SHS is: soft structure provided the possibility of creation (by randomness and evaluation), while hard structure can maintain creations and keep evolution in a certain direction.

3.2 Learning Scheme

Cognitive learning is a process of evolution. The machine has to adjust itself according to the change of environment constantly. From this view point, soft-hard structure theory can shed light on the problem of bootstrap and adaptive learning.

Given some basic evaluation criterion, such as the chance to feed and the time to complete a task, the bootstrap process can be done by "soft learning". When having to finish a task without any prior knowledge, a clear choice is to try randomly. Once a good result is found, this experience is recorded, "hard learned (modeled)" into hard structure. After enough accumulation of trials, the machine will have enough experience to do more complex jobs. And further knowledge can be derived based on these experiences.

Adaptive learning can also be achieved by interactions between soft and hard structures. As a prior, the system has to be able to detect the inconsistency between new experiences and prior models, or the contradiction between existing models. Usually, the system uses existing knowledge (models) to go through ordinary jobs. When new contradicting experiences are gained, soft structure will decide how to deal with them: modify models, or build a new one. And when the inconsistency between models in the hard structure grows to a certain level, those models will be extracted back to the soft structure for further operation. Thus the system's knowledge can be updated as needed.

3.3 Soft-Hard Memory Infrastructure

In order to facilitate the learning scheme proposed above, we designed a soft-hard memory (SHM) infrastructure. In SHM, memory is divided into two parts. Soft memory (SM) provides an active data storage for the soft learners. It primarily stores direct, concrete materials that is perceived or generated by the system. Information in soft memory will be forgotten soon. Hard memory (HM) is a static and persistent database for the system. Information in hard memory is more important and highly condensed, such as basic value functions, learned models and concepts. These information is the core of hard structure and will not change unless obsolete.

Interactions between SM and HM are realized through proper learning algorithms. In principle, the soft learner uses functions and models from HM to examine the information in SM. When experiences are recognized as new knowledge, the hard learner will build new models. When inconsistency in HM is detected (e.g. when results from models contradicts with each other), those inconsistent parts will be extracted back to SM, either to be modified, fused or discarded.

Actual forms of SM and HM are not specified here. People can, and should, design particular storage scheme with regard to requirements. For example, SES [1] can be used for SM, and a ordinary relational database is already competent for simple learning tasks.

The configuration of SHM is quite similar to traditional short-term/long-term memory. Their functions do overlap a lot. However, SHM is designed from the perspective of evolution, while most other architectures are from the point of psychology or information processing.

Soft-hard memory possesses many merits besides its bootstrap and adapt abilities. First of all, SHM is intuitive and compatible with common cognitive knowledge. It is similar to the classification of memory in psychology, and the working process is very clear. Secondly, this structure is flexible and can be readily extended. Actually there is no limitation on the number or the form of concepts, and all information stored can be changed as necessary. Thirdly, the conflict of vast information and processing speed can be well balanced under this structure. SM can work as a buffer of information. Data in it can be processed when the system is not busy, so the load of the machine will not fluctuate dramatically. Finally, it can be easily implemented as a parallel running system. This framework enables physical separation of memory system and other modules (such as reasoning). So the speed and scalability is guaranteed.

4 Application

4.1 Cognitive Robot Project Overview

In the cognitive robot project, we are planning to build a intelligent robot system to accomplish the following tasks:

Identify people: The robot will first identify the person appears in the camera as stranger or an acquaintance. Face images are used for recognition.

Learn acquaintance: If the robot sees a stranger for many times, it will turn him/her to an acquaintance.

Move to the target site: When a task is confirmed, the robot have to choose a route and move to the site. Possible obstacles must be avoided efficiently.

Fetch an object from the person: The robot will use its robot arm to fetch a specified object from the person's hand. Optimum motion sequence should be adopted.

During the process, this robot will use past experiences to solve current problems. This involves intensive learning. Furthermore, all these tasks have to be finished in a real-time situation. To do this, we will use the learning scheme in section 3.2 and SHM as its primary data storage.

4.2 Learning of acquaintance

In this task, the robot has to learn to know people. At first, all the people are strangers. As the robot sees a person for certain times, it will classify him/her as an acquaintance. This is a basic cognitive behavior.

The identification of people is accomplished by face recognition. We use Bayesian Face Models [6] (BFM) for this task. In BFM, face images are used as training samples (prototype). When a new face is perceived, the system will calculate the probabilities that this new face is the same as each prototype. If no probability is high enough, it is rejected as belongs to no one. There are two key components in BFM: prototypes and the probability model, which are both stored in HM.

This module runs as follows: all perceived faces are initially stored in SM, and then soft learner will identify them using prototypes and probability model from HM. If a face is rejected, hard learner will turn it into a new prototype in HM. By continuously adding prototypes, the robot's knowledge about people keeps growing. We call this process "absorbing".

When the prototype set in HM changes, the probability model, which is calculated from prototypes, should be updated too. However, since the updating process is very time consuming, we can not do this on every change. Instead, when the system is idle, a monitoring thread will extract prototypes from HM to SM. Then a new model is learned and stored back to HM. Besides, because BFM is not perfect, there must be some redundancy or even mistakes in the prototype set. The system will refine it as necessary. We call these activities "reflection", which is in fact processes that reconstruct the knowledge. By using "absorbing" and "reflection", this system can learn acquaintances adaptively.

4.3 Learning of action

In order to fetch objects from peoples hand effectively, optimized motion sequence of the robot arm has to be learned. Compared with learning of people, this is a more complex job, and we are still improving it.

At the beginning, the robot will try randomly (basic heuristic guide may be incorporated for efficiency). Current environment and all the action/result pairs are stored in SM. Then the data are used to learn a model that can make decisions according to current environment configuration. On the low level, motion sequences to finish a basic action will be learned; on the high level, the robot has to make general decisions according to environment. In general, this is still an absorb/reflect process. Now, actual learning method for motion sequences is under consideration.

5 Conclusion

Based on soft-hard structure theory, we propose a cognitive learning scheme and its corresponding memory structure. They are designed from a evolutionary view point. Using them we can hopefully realize a cognitive learning machine, which is a machine with bootstrap ability and can learn adaptively. However, this proposal is still a conceptual guideline for the design of practical systems. Details have to be specified and implemented according to actual requirements. In our project, this guideline can be well suited into concept and action learning tasks.

Soft-Hard structure theory is a powerful foundation for developing evolutionary machines. In the future, more functional parts of the robot project will be designed based on it.

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