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Machine Knowledge and Human Cognition

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Machine Knowledge and Human Cognition

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Abstract: Intelligent machines are knowledge systems with unique knowledge structure and function. In this paper, we discuss issues including the characteristics and forms of machine knowledge, the relationship between knowledge and human cognition, and the approach to acquire machine knowledge. These issues are of great significance to the development of artificial intelligence.

Key words: intelligent machine; machine knowledge; human cognition; knowledge interpretation; principle of functional similarity; Probable Approximative Correction (PAC) model

1 Introduction

Artificial Intelligence (AI) plays a key role in driving social development. Intelligent machines have been widely used as an important part of productivity. They can judge, predict, and adjust their behaviors according to the change in environments. Accordingly, intelligent machines are regarded as knowledge systems, in which knowledge generation and identification are different from those in human beings. This type of knowledge is called machine knowledge. In this study, preliminary explorations were made to understand the knowledge in intelligent machines, the relationship between machine knowledge and human knowledge, and the use of machine knowledge to better understand the world. The rest of this paper is organized as follows: In Section 2, we discuss the definition of machine knowledge, propose the concepts of elementary and advanced knowledge, and discuss the relationship between them. In Section 3, we discuss the forms of machine knowledge and expound some assumptions for machine knowledge. In Section 4, we describe the methods and viewpoints to acquire machine knowledge. In Section 5, we conclude this paper.

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2 Knowledge and Machine Knowledge

Knowledge has various descriptions and definitions. We think that a good definition must satisfy two aspects: Firstly, the concepts involved in the definition should be obvious and easy to understand. Secondly, the definition should be easy to be tested and applied.

Our definition is based on the system theory, where a system consists of objects and change rules between objects. Each object has finite or infinite levels. At a fixed time, each object is at a level. The set of all object levels at a given time is called the system state. The system states, together with the changes between states, are called phenomena. The change rules of phenomena form the content of most scientific researches. This is the system theory in scientific research.

Generally, knowledge can be classified into elementary knowledge and advanced knowledge. The direct description of the changes between systematic phenomena is called elementary knowledge. The knowledge formed by the inference process and induction of elementary knowledge is called advanced knowledge. Advanced knowledge reflects the internal law and universal principle of the transformation of system phenomena.

Knowledge can be abstracted and sorted out gradually, which reflects the cognitive level between changes in phenomena. In other words, knowledge is hierarchical, and knowledge at each level is the scientific induction or common internal law of the knowledge at the lower levels. The higher the level of knowledge, the higher the scientific value and artistic appreciation it has, and the deeper the links of levels between phenomenal changes that can be reflected. In the current structure of human knowledge, causality is at the top of knowledge. Human beings tend to discover and explain the causality of changes in system phenomena, but this case is not always feasible. The process of acquiring knowledge (including elementary and advanced knowledge) through observations is called knowledge cognition or interpretation.

The above description of knowledge is the systematic definition of knowledge. If the object is represented as a set of attributes and the level of the object is represented by the values of the attributes, then the relationship between the objects can be reflected by describing the changes of attribute values. This process is called ontological knowledge description. Human beings use other ways to describe knowledge, such as formal description and empirical description. In fact, several methods of knowledge description can be transformed from one to another. At present, knowledge description is mainly based on the system theory and ontology theory, whereas other descriptions lack integrity and rigor.

This definition of knowledge is also applicable to trained intelligent machines.

The internal states of intelligent machines are constantly changing during the operation. In particular, after giving the input, the machine can give corresponding outputs, which are phenomena and changes of phenomena. Therefore, intelligent machines also contain knowledge, which are in fact laws reflecting phenomena changes, especially the law of changes between the input and output.

Two steps are needed to acquire knowledge from systems or intelligent machines: (1) observation and perception and (2) induction and description.

Observation and perception are the acquisition of the system state, which are divided into physical perception (real object) and abstract perception (symbolic object). In physical perception, the object of the system is an objective source, and its states and changes can be observed through physical means (e.g., human senses). In abstract perception, the object of the system is symbols or data, and its state and changes are expressed in symbolic form. At present, the vast majority of observation information is presented in the form of data, even for physical observation. Therefore, knowledge or knowledge recognition can be developed at the data level. This method is called data-based knowledge acquisition or knowledge expression.

Because human beings cannot identify the infinite state and identifying the infinite state in applications is not necessary, it can be assumed that the system or intelligent machine is finite (discrete). In this case, a system or intelligent machine is actually equivalent to a Structure-Changeable Finite Automata (SCFA).

SCFA is a variant of finite automata, which is used to represent the system state and state changes. The system states are represented by nodes, and the possible changes between states are represented by arrow lines. During operation, the connections between states can be changed. These changes obey some computable rules. In SCFA, the number of states is limited, so the phenomena (the changes between states) are also limited, and the total amount of primary knowledge is limited. This assumption about the limited amount of knowledge is very important in the study of AI. From the view of SCFA, the capabilities of intelligent machines can be summarized as follows:

(1) Given a state collection A, what is the subsequent state? (what is)

(2) Given a state collection A and a state B, is B reachable from A? (what if)

(3) Given a state collection A, what is its predecessor? (why)

These problems are the basic problems of AI. The solutions for the first, second, and third problems are called weak intelligent machines, strong intelligent machines, and true intelligent machines, respectively. This description is basically consistent with the three steps of AI presented by Pearl[1].

3 Form of Machine Knowledge

From the viewpoint of the system theory, a learning model, a natural system, and a social group all have changes between states, some of which are internal and some are generated by interactions with the surrounding environment. When a machine is given intelligence, such as a learning machine after reasonable training and learning, it can predict and describe the relationship between phenomena, so it acquires knowledge. All knowledge in an intelligent machine belongs to latent knowledge before human interpretations and then to explicit knowledge after perception (physical or computational perception) and description.

For example, the research activities in physics are divided into two parts: observation and induction. Generally, we obtain phenomena and their correlation through observations and then summarize them into unified and regular forms through abstraction. The higher the level of abstraction, the more universal and basic the knowledge is, hence attracting more attention. In physics, knowledge, such as Newton's law and Maxwell's equations, reveals the universal laws of motion and electromagnetic phenomena in natural reality and points out the logical connection and causal evolution between these phenomena. Such knowledge belongs to the top knowledge of human beings.

Machine knowledge aims to better understand how intelligent machines work, what they are based on, and how to predict and judge, which are necessary for us to believe that machines can make decisions. Because the knowledge representation formed inside the machine is almost unknown, we can only guess its internal form according to its external performance, causing general confusion. The structure and related parameters of a learning model can be known theoretically, and such a model can also be regarded as a function $(\theta_1, \theta_2, \ldots, \theta_k, x)$, where $\theta_i, i = 1, 2, \ldots, k$ are the parameters and x is the input. However, in most cases, although we know the structure and parameters of the intelligent machine, we cannot predict its behavior, just as we cannot judge how it will think according to the neural connection structure of the human's brain. For example, although AlphaGo[2] has successfully defeated human beings in intellectual games, its operations can be simulated by a Turing machine, and its structure and parameters can be adjusted. However, two important factors have made AlphaGo cryptic.

Firstly, although people can manipulate the initial static structure and parameters of AlphaGo, its structure and parameters in the continuous evolution of the learning process cannot be predicted.

Secondly, in terms of operational efficiency, AlphaGo is much faster than human beings. Hence, even if human beings know the structure and parameters of AlphaGo, there is no way to fight against this computer program. Therefore, the real mystery of AI machines or what humans are not yet able to control, is their evolutionary ability.

Another goal for human beings is to acquire machine knowledge. Thus, they need advanced knowledge rather than elementary knowledge. This process ensures that human beings can overcome the inherent weakness of slow operation efficiency and win initiatives in coping with the changes of the living environment and recognizing natural laws. Therefore, in many cases, it is not that we cannot acquire the knowledge on intelligent machines, but that we cannot interpret the knowledge of intelligent machines in the way that human beings are accustomed to at present. Machine knowledge is basically in the form of an association, and we can easily acquire such knowledge. Human knowledge building is organized and constructed by logic and causality, but machine knowledge does not have such a form at present. That is, physical identification is easy, but causal modeling is difficult. Therefore, there is an urgent need to find new theories and methods to express machine knowledge as a form that can be understood and applied by human beings. That is, to adapt to the scientific system constructed by human beings for thousands of years, we need to express machine knowledge based on logic and causality.

4 Acquisition of Machine Knowledge

In this section, we discuss a very practical problem, that is, how human beings can acquire machine knowledge. As mentioned before, human beings and machines have different knowledge structures and systems. How to connect these systems and make them understand each other are the most interesting and basic problems in the research and application of AI. According to Pearl[1], if robots are black box systems, such as AlphaGo, we cannot talk with them meaningfully, which is an unfortunate thing. In this section, we discuss how to translate machine knowledge into human knowledge and its methods, boundaries, and scope.

Again, we take physics, which is a classic science that uses causality to interpret the natural world, as an example. The natural world can also be seen as a huge intelligent machine, in which phenomena are changing every moment. In recognizing these changes and their laws in the natural world, human beings adopt the form of causality description to give a clear and accurate expression of the law behind the phenomenal transformation. Its form mainly adopts the regular and mathematical expressions, so people can not only describe the phenomena that have occurred but also predict the possible phenomena, and the latter is particularly important. Because the actual operation law of the natural world cannot be directly obtained, human beings can only "guess" the internal law through phenomenal observations. Even if a large amount of observation data have been accumulated, it may be quite difficult to sum up the corresponding law completely and accurately. Therefore, two principles (or beliefs) are used in the interpretation of the natural world, which are clearly expounded in Newton's *the Mathematical Principles of Philosophy of Nature*, Volume 3 ("Systems of the Universe"), which discusses the first two of the four "rules of reasoning in philosophy":

(1) Minimalist description principle (Oakam's razor): Nothing can explain the causes of natural things better than those who are real enough to explain their phenomena.

(2) Principle of functional similarity: For the same natural phenomena, we must try our best to find the same reasons.

For physics, some fundamental laws and principles follow the two basic principles mentioned above[3]. Through reasoning and induction, people's understanding of the basic laws of the natural world and the building of human natural science are formed.

In AI, we need to add a third principle:

(3) Invariance hypothesis: The internal change of intelligent machines is controlled by the most basic computable laws, and these laws are invariable in a given period of time[4].

The invariance hypothesis proposed by Valiant[4] states that the internal laws governing the change in intelligent machines are invariable in a certain period of time. Of course, these laws themselves may change over time. We will mainly discuss this kind of intelligent machine, which satisfies the assumption of invariance. This kind of intelligent machine can theoretically be simulated by a Turing machine.

At present, the vast majority of machine learning is in the statistical induction mode. Intelligent machines trained by data mainly reflect the related knowledge of data, so they belong to elementary knowledge. To obtain high-level knowledge with general and universal rules from specific primary knowledge, corresponding calculations are needed. These calculations are based on specific cases to obtain the general rules hidden behind the cases. For such algorithms, the understanding is not very deep, many problems need to be further solved, and there is no general theory at present. Valiant[4] believed that the mathematical logic that gave birth to computer science was not enough to explain this process, so we need to find new theories.

For uncertain intelligent machines, especially complex systems where chaos may occur, small input errors may cause large fluctuations in the observed results, which increase the difficulty of cognition and even become infeasible. Particularly, determining whether a system has chaotic properties is not feasible. Therefore, how to obtain accurate observation results and interpret the knowledge of uncertain complex systems is a very difficult problem.

In general, the effective way to interpret an uncertain intelligent machine is Probable Approximative Correction (PAC) model[4], which interprets and acquires the knowledge contained in the uncertain intelligent machine with certain reliability $1-\delta$ and error ε. PAC combines the characteristics of a random algorithm and approximation algorithm and uses two measures, i.e., confidence (the possibility of outputting approximate results) and approximate error (the approximate degree of calculation and real results). PAC method is applicable in many fields, such as biological systems. When a previous generation imparts knowledge to the next generation, it does not utilize all the knowledge to train the next generation. The next generation only learns part of it (the main content of courses) and may study errors in the learning process, but such method does not affect the next generation's capability to inherit knowledge and innovate. In the process of human learning, many skills can be acquired by imitating and learning a few cases. This is the knowledge learning method of PAC.

At present, many machine learning theories are based on the PAC method.

In addition to learning association patterns from concrete examples (i.e., data), people also pay attention to directly learn causality from data. This method was developed by Rubin, Pearl, and Granger[5] after the 1970 s. These methods have pioneered the quantitative analysis of causality. Up to now, causality is still the fundamental cornerstone of human understanding of the natural world, and the relationship described by probabilistic thinking is the surface phenomenon that promotes our understanding of the causal mechanism of the world. Pearl and Mackenzie[6] said, "Probabilistic thinking is essentially trying to estimate, using some tools of math and logic, the likelihood of any specific outcome coming to pass. It is one of the best tools we have to improve the accuracy of our decisions. In a world where each moment is determined by an infinitely complex set of factors, probabilistic thinking helps us identify the most likely outcomes. When we know these, our decisions can be more precise and effective." The first point is the fact that scientific knowledge is not expressed in the form of probabilistic thinking, but in the form of causal thinking. The second point is how to conduct causal thinking. Pearl and Mackenzie[6] believed that human beings had not invented a mathematical tool to describe causal thinking. However, most popular intelligent machines run in a probabilistic way, and the relationships between the phenomena are all related. Can we decipher the causality hidden in these relationships? In theory, Rubin, Pearl, and Granger's method can obtain causality from a large amount of data through a graph model or potential result analysis[5]. However, in fact, at present, this method requires a high quantity, distribution, and quality of data, which is difficult to guarantee in most cases.

Therefore, it needs to be further developed and perfected. Besides calculating causality, these methods can also reverse it. Fact reasoning, incomplete experiments, causality burdens of proof, and other calculations have very practical applications in the fields of medical diagnosis and nursing care for the aged. Some studies using AI technology in this field show that, on the basis of collecting large-scale clinical data, causal analysis can be achieved by properly designing models to acquire good results and even obtain new phenomena and causality.

With the steady development of causal computing, another more popular method, the interpretability of machine learning, is booming. If a machine has been trained and the test results are good, then can we use it safely? If we input all physical examination data into a deep neural network, will it make a diagnosis for you and give a prescription? Because we do not fully recognize the machine, it is difficult to build trust in it. People need to know how the machine works and the principle of forecasting, which requires that machine knowledge should be interpretable. Generally, the interpretation of machine learning aims to acquire the deep hidden knowledge behind the learning model and learning results through in-depth mining. This knowledge can be used to evaluate the performance of the learning model and reflect the deep internal relationship between data, even the causal relationship. In the diagnosis of epilepsy, the neural network method is used to find the maximum eigenvector through a mathematical analysis of the model. Clinical experiments have found that the vector corresponds to the lowest frequency of Electroencephalogram (EEG) generation and can be used to detect epilepsy lesions, which shows that the machine knowledge is interpretable, and the results of interpretation are related to human knowledge.

Traditional reasoning systems are often based on models and algorithms. Starting from data, they are generated iteratively. Because of the transparency of reasoning rules, such reasoning systems can be interpreted. However, for opaque intelligent machines, such as neural networks or the Monte Carlo tree search, knowledge cannot be acquired through interpretation, especially advanced knowledge. Therefore, the corresponding algorithms should be examined to obtain different levels of interpretation. Through this progressive way, advanced knowledge can be discovered, and the unity of human reasoning and machine reasoning can be achieved.

Other approaches are derived from physics. When the causality of the natural world is difficult to understand, physics also assists human research through machine learning methods, such as the Langevin equation of multibody systems and the Boltzmann description of the Liouville equation (BBGKY truncation). The use of intelligent machines to interpret intelligent machines is a wonderful idea. In fact, various intelligent machines (or learning models) are hierarchical in transparency. Some intelligent machines are more transparent to human beings, such as linear models and decision tree models, and some intelligent machines are black box to human beings. Unfortunately but meaningfully, a black box intelligent machine generally has a stronger learning ability and richer knowledge[7]. If it is difficult to directly interpret an intelligent machine, then we can interpret the less transparent intelligent machine through a more transparent intelligent machine. In this process, we need to use the principle of functional similarity. If M is a less transparent intelligent machine, it has a high accuracy in the prediction and judgment of phenomena. That is, it has a good output response to the input data. We can actively input some data x to get the corresponding output y, so as to derive the data (x, y). y will be regarded as an annotation, and a relatively transparent learning model T is chosen using these annotated data to train model T. If the training is successful, according to the principle of functional similarity, then T becomes causal to M to a certain extent, so interpreting T is equivalent to interpreting M. We can use a machine that is easy to explain to simulate the machine that is not easy to explain. This process can be recursive, making the interpretation content more easy to realize, thus gradually reaching the form that humans can understand, which opens up the automatic mode of understanding machine knowledge.

For example, AlphaGo Zero is generally a machine knowledge system that is not yet understood. It generates a method of judging the situation of Go and corresponding game strategies through its own training iteration, decision-making steps, evaluation steps, and enhanced learning. The knowledge contained in AlphaGo Zero is different from that accumulated by human beings for thousands of years (so-called “chess theory”). AlphaGo Zero has its own chess theory and rules, so interpreting AlphaGo’s elementary knowledge into advanced knowledge that human beings can understand and apply is a core and difficult problem. Furthermore, designing an automated way to achieve this process is a fundamental challenge for AI research.

5 Conclusion

At “the Symposium on Machine Knowledge and Human Cognition” held in Lanzhou University in July 2019, 13 experts in physics and computer science were invited. This paper was formed on the basis of gathering and sorting out the experts’ opinions. From the definition and description of machine knowledge, the basic problems of human cognition, and the relationship between machine knowledge and human cognition, experts put forward good views and methods from their respective fields.

Machine knowledge is the knowledge contained in intelligent machines. In the intelligence era, these knowledge and human knowledge form the cognition of various natural and social problems. Machine knowledge is a supplement to human knowledge and broadens humans’ ability and means of recognizing nature. How to transform machine knowledge into a form that human can understand and conform to the expression habit of human knowledge is undoubtedly a challenging problem, which is of great significance to humanity’s development. If human beings and intelligent machines cannot communicate and understand each other and human beings cannot effectively interpret the knowledge of intelligent machines, then the development of AI will encounter great obstacles, even hidden dangers.

To sum up, we should adopt multidisciplinary cooperation to strengthen the theoretical research on machine knowledge and design creative algorithms to help people better understand intelligent machines and its capability of making accurate predictions, so as to understand its performance limits and optimization degree, security scope, and application limits. In a word, through the reliable interpretation of the knowledge inside intelligent machines, people can trust the machines more and establish a good communication and interaction relationship with them. This core problem must be actively solved in the process of AI development.

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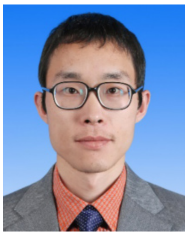

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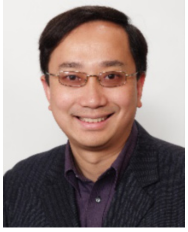

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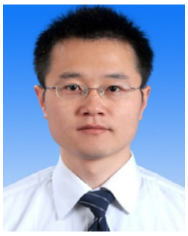

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