Neuro Symbolic Artificial Intelligence

Pioneer to Overcome the Limits of Machine Learn

by

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ABSTRACT

With the recent boom in artificial intelligence, various learning methods and information are pouring out. However, there are many abbreviations and jargons to read without knowing the history and development trend of artificial intelligence, which is a barrier to entry. This study predicts the future development direction by synthesizing the concept of Neuro symbolic AI, which is a new direction of artificial intelligence, the history of artificial intelligence from which such concept came out, and applied studies, and by synthesizing and summarizing the limitations of the current research projects. It is a guide for those who want to study neural symbols. In this paper, it describes the history of artificial intelligence and the historical background of the emergence of neural symbols. In the development trend, the challenges faced by the neural symbolic, measures to overcome, and the Neuro Symbolic A.I. applied in various fields are described. (Knowledge based Question Answering, VQA(Visual Question Answering), image retrieve, etc.). It predicts the future development direction of neuro symbolic artificial intelligence based on the contents obtained through previous studies.

DEDICATION

To my family, homeland, and God who always give me a strong support

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 Research Background and Motivation

After AlphaGo AI defeated former 2016 Go champion Sedol Lee. People was shocked. Because Go was a board game with so many variables that computers could not beat humans. Interest in artificial intelligence has increased. It was a historic event. After the historical event, there was a boom in research into artificial intelligence. In particular, the interest in deep learning, the learning method of AlphaGo, has exploded. Along with research on deep learning, research on artificial intelligence also began to build momentum.

1.2. Objective

In this paper, in order to overcome the limitations of artificial intelligence and develop it, we examine the challenges of today's artificial intelligence and study the direction of its development. It will be worthwhile to learn about 'Neuro symbolic AI', which has characteristics that can overcome the limitations of artificial intelligence including deep learning. By introducing the background, concept and characteristics of Neuro Symbolic, and the projects currently under study, it helps those who are new to it to understand the concept, research trend, and development direction of Neuro Symbolic AI, so that you can apply it to your research field.

1.3 Organization

Chapter 2 explains the concept, background of appearance, and characteristics to help the overall understanding of neuro symbolic AI. In 2.1, the background of the emergence of Symbolism AI and Connectionism AI in the history of artificial intelligence, the challenges encountered and how to overcome them are covered. In 2.2, we explore the features and limitations of today's artificial intelligence. In 2.3, we will look at what Neuro Symbolic AI is, why it was created, and what its features are.

Chapter 3 explores the latest research trends in Neuro Symbolic. Among the five-year papers at major conferences (in ICML, ICLR, AAAI, NeurIPS, and CVPR), it will introduce interesting research related to Neuro Symbolic and a sweet spot for artificial technology development.

Chapter 4 examines the strengths, weaknesses, and limitations of Neuro Symbolic AI, which were covered in Chapters 2 and 3, and discusses the future development direction.

CHAPTER 2

NEURO SYMBOLIC ARTIFICIAL INTELIGENCE

2.1 History of Artificial Intelligence

In 1950, Alan Mathison Turing published a paper called 'Computing Machinery and Intelligence' and the concept of artificial intelligence(Turing & Ince, 1992) was officially introduced to the world. In that paper, Turing proved that machines can be intelligent. However, even at that time, the word artificial intelligence did not appear directly, and there was no specific content. However, six years later, John McCarthy of Dartmouth University mentioned the term 'Artificial Intelligence' at a Dartmouth conference(McCarthy et al., 2006) and suggested specific discussions and research, and research on artificial intelligence began.

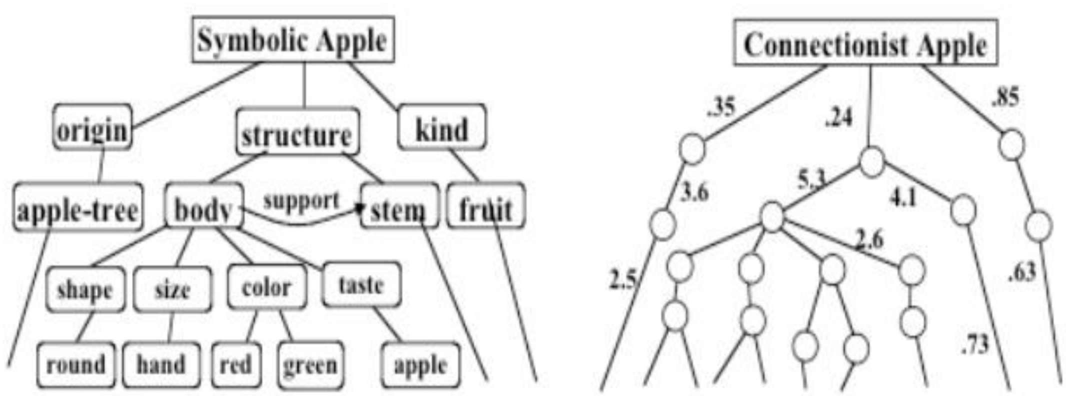


Figure 1 Numerical Opacity: Symbolic Apple vs. Connectionist Apple From

There are two major schools of research on artificial intelligence: Connectionism and Symbolisms. Connectionism is a school of thought that emulates the structure of the human brain and implements machine intelligence(Fodor & Pylyshyn, 1988). The reason why it is called connectionism is because the brain neural network has a structure in which multiple neurons are connected by synapses. In other words, the name 'connectionism' was given because neurons implement connections and synaptic connections. In particular, in 1958, ‘Perceptron’ was published(Rosenblatt, 1958), which was about a computer algorithm modeled after a neural network in the brain. Since then, connectionism has been the subject of many discussions to develop artificial intelligence based on the perceptron. However, it has failed to implement a process in which humans acquire intelligence through experience and learning. It was because there was not much learning data at the time, and computer performance could not support it. In addition, the AI winter started by pointing out the problems and limitations of the perceptron in a book called 'Perceptron' published by Marvin Minsky and Seymour Papert in 1969(Minsky & Papert, 2017), and in 1973, Professor James Lighthill of the UK Announcing the limitations of the research(Lighthill, 1973), most AI research has been dismantled or has gone through an AI winter where funding is difficult.

On the other hand, the signal to logically express knowledge by symbolizing it and to solve problems has continued the development of a series of 'Symbolisms'(Garnelo & Shanahan, 2019). Computers have fundamentally developed various logics and algorithms with '0's and '1's. They thought that artificial intelligence should be implemented in the way that computers work, and in order to make logical inferences using artificial intelligence, computers need knowledge Thinking that it should be possible to express in an understandable language, we developed languages used in computers such as

LISP(Winston & Horn, 1986) and Prologue(Szymanski, 1988). Among them, the LISP (List Processor) facilitates the programming operation of symbolic expressions to provide structured data. It refers to a method of representing in human-readable text form by making it into a symbolic expression. By expressing and storing logic in a language that computers can understand, we were able to solve the Tower of Hanoi puzzle using Logic Theorists, one of the symbolic languages. This has popularized the so-called ‘expert system’. An expert system is a program that stores knowledge in a specific field, and the computer applies logical laws to derive answers through deductive and inductive reasoning similar to humans(Cohen, 1985; Becraft & Lee, 1993). Among them are DENDRAL, where a well-known system was developed to infer chemical molecular structures, and MYCIN, which diagnoses blood diseases. However, although expert systems have superior storage and reasoning capabilities than humans in certain areas, they are expensive to develop and inefficient because the computing power required for storage and operations is not supported unlike the present. The spring of AI, which came to us as an expert system, has disappeared again, and the second winter of AI has arrived.

Even in the dark ages, scholars have overcome the challenges that need to be solved in developing artificial intelligence and have improved computer performance and algorithms that can practically implement deep neural networks proven only mathematically. First, the XOR logic problem pointed out in the perceptron could be solved by neural network(Piramuthu et al., 1994). The explosive growth of hardware, which doubles the performance of semiconductor integrated circuits every two years according to Moore's law, has overcome the limitations of the past and made possible the implementation of efficient and feasible AI. In particular, in 2006, when Geoffrey Hinton proposed a deep neural network technology (Deep Learning) based on Deep Belief Network, the potential for practical use began to be seen, and it attracted a lot of attention from the academic community(Hinton & Salakhutdinov, 2006; LeCun et al., 2015). From then on, the name was changed from 'Neural Network' to 'Deep Learning'. In addition, Deep-CNN (Convolution Neural Network) showed remarkable results in image recognition performance evaluation. The error recognition rate fell from 26% in 2011 to 3.5% in 2015, and the recognition rate dropped sharply in 4 years. At the same time, the realization of the technology Looking ahead, Google acquired Deep Mind Technologies in 2014. After that, in 2016, he defeated Sedol Lee (Former GO champion) with AlphaGo 1.0 (supervised deep reinforcement learning based on supervised learning and probabilistic sampling-based decision making), and a year later, with AlphaGo 2.0 (self-learning based on small amount of unsupervised learning) defeated Professional Go player of 9 dan rank, Ke Jie. The victory over the Go players has provided an opportunity for AI technology to be recognized and re-evaluated by the general public. The AI technologies proposed so far are CNN, RNN (Recurrent Neural Network: a neural network strong in speech and text fields)(Cho et al., 2014), and GAN (Generative Adversarial Nets: learning to improve performance by 'adversarial' between models that generate images and various models concept)(Mao et al., 2017), and as 'reasoning' research, which seemed to have no practical potential, began to show results, Neuro Symbolic AI appeared.

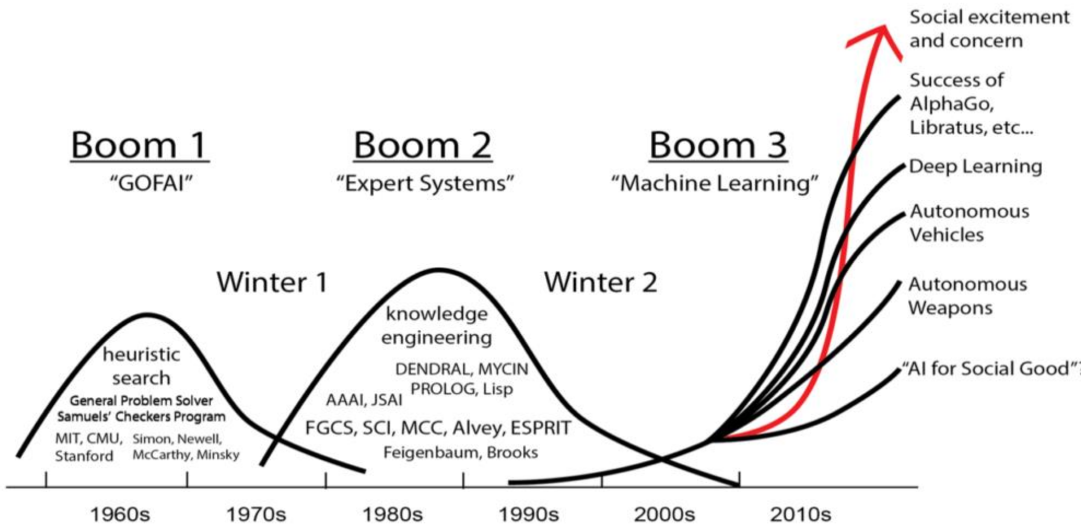


Figure 2 The Three Booms of AI, an original diagram inspired by Yutaka Matsuo

2.2 The Challenges of Artificial Intelligence Today

Although deep learning is being used in every aspect of our lives, there are still many areas to be developed. First, artificial intelligence, represented by deep learning, learns and predicts based on given data, so the prediction rate is low for contents that are not in the training data and unexpected variables(Reichstein et al., 2019). Most of AI success cases such as AlphaGo perform better with fewer environmental disturbances. In other words, it was effective in an under-controlled environment. For example, DeepMind's AlphaGo, a representative case of reinforcement learning, also showed good performance under controlled conditions, such as a computer game called Go. On the other hand, there are numerous environmental disturbances in the reality we want to use in real life. For example, in Korea, it was attempted to apply the electronic nose technology fused with a low-cost sensor and AI as a method of automatically monitoring the leakage of harmful gases, but it was difficult to implement due to high environmental disturbance and high performance (high resolution) of the equipment. For example, hazardous substances are determined by the output value of the gas sensor. However, even if there is no gas, the output value of the gas sensor increases when the temperature or humidity changes, resulting in an erroneous notification that it is a harmful gas. In addition, it was difficult to mathematically model the effects of temperature and humidity because of the combination of sensor performance degradation and H/W uncertainty factors over time. Therefore, through this case, how to machine-learning environmental disturbances and uncertainties is a task for robust and practical artificial intelligence technology. In addition, there is a problem that occurs because learning is performed efficiently based on the learning data.(Garcez et al., 2008)

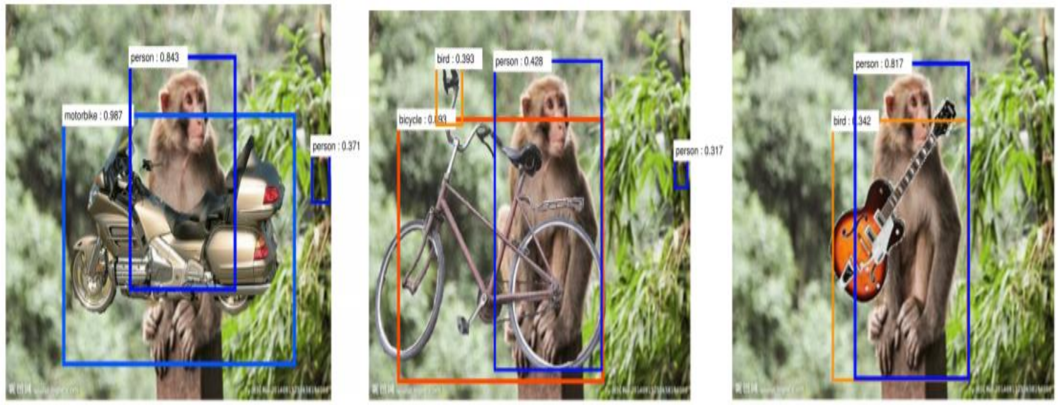


Figure 3 Adding Occluders Causes Deep Network to Fail From Wang et al. (2017)

If you look at the monkey picture in Figure 3, it shows that deep learning fails when an occluder is added. In the picture on the far left, the motorbike made the monkey recognize the monkey as a person, in the middle picture the motorbike made the monkey recognize the monkey as a person, and the jungle made the handle a bird. In the right panel, the guitar turns the monkey into a man, and the jungle makes the guitar a common sight in the tropics recognize the orange bird. In other words, the over-fitting problem according to the visual context occurred and it was prevented from looking at the object as it is. If there was no motorbike, it would be recognized as a monkey, because there was no data set with a monkey and a motorbike in the existing training data, and a person with a motorbike was learned, so it was predicted as a person rather than a monkey according to the context. Through these experiments, Wang said that deep networks are difficult to analyze because they are black boxes, and their ability to adapt to new data (which has not been previously dealt with and untrained) is limited(Wang et al., 2017).

In this example, we did not feel a significant life threat, but if AI is applied in everyday life without being robust, it can be a great threat. David Cox addressed the black swan problem (an unpredictable or unforeseen event, typically one with extreme consequences) of existing artificial intelligence in a lecture at MIT and explained the challenges that artificial intelligence must overcome(Cox & Dean, 2014).

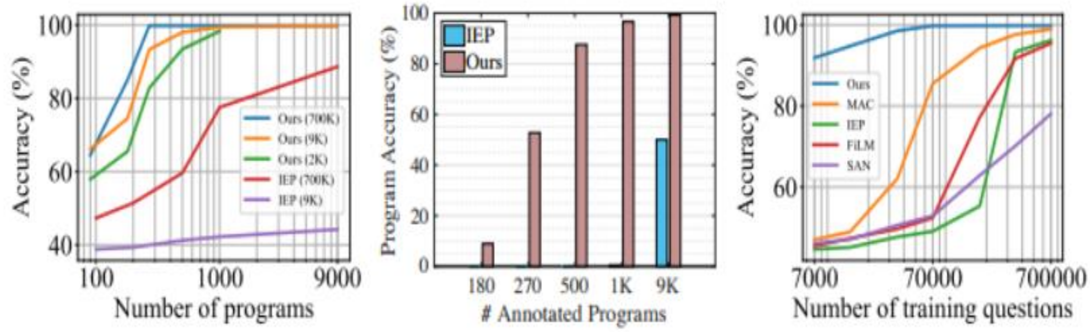
For example, you are waiting at a traffic light on a New York crossroad. Then suddenly a group of buffalos appeared. If you were on a Tesla or Waymo, would the AIs have recognized this situation? Cox said the AI probably was not aware of this situation, the buffalo itself. Similar to Wang's experimental results, the existing deep learning-trained models would have been trained with data centered on frequently occurring events for efficient learning and would have been trained based on existing data. Did the data show any wild beasts of buffalo in the city? You probably did not realize it. So, there is a high probability that it will not react properly. In this case, if you just look at the traffic lights and move as you have been taught, you will collide with the buffalo, which can lead to a serious accident leading to death. If so, can we make and learn these examples? We don't have enough data to realistically train, test, and solve black box vision algorithms(Papernot et al., 2017). Therefore, the direction of the next generation of artificial intelligence is to have the ability to generalize and 'reasoning' even if there is little data learned like humans.

In other words, the current challenges facing artificial intelligence, summarized in the above cases, are as follows. Because the predicted value is greatly affected by the learned data, the accuracy is greatly reduced when unexpected situations and variables occur in reality, and it is vulnerable to adversarial attacks, edge cases, and black swan problem(Papernot et al., 2016). It also requires a lot of data and uses a lot of computational power for training. (Najafabadi et al., 2015),(Chen & Lin, 2014),(Chen & Lin, 2014). Since all these processes are black boxes, they cannot explain intermediate processes that humans can understand.

2.3. The Emergence and Characteristics of Neuro Symbolic AI

The conclusion we draw from the challenges of artificial intelligence discussed in 2.2 is that if Artificial Intelligence use learning and 'reasoning', like humans, then the development of artificial intelligence will be rapid. Neuro symbolic combines the strengths of the two in order to make inferences based on the existing neural networks optimized for learning, that is, deep learning, and learned through symbolic representations in this background. To achieve effective integration of learning and reasoning, the two fields of symbolic reasoning and statistical learning must be effectively combined.

Neural Symbolic solves the problem of neural nets called 'propositional fixation'. Also, most of knowledge expression and learning focused on the variable-free part. However, scientists have proposed some alternatives to the formalization of variable bindings, and solutions that deal with the expression of relationships. In addition, generalization of abstract expressions in deep learning was a basic goal, but they did not understand how abstraction happens. However, under the concept of Neural Symbolic Computation, neural networks have contributed to the creation of explainable artificial intelligence by providing a level representation of symbolic abstraction (Gunning et al., 2019; Samek et al., 2017). Existing neural nets have dealt with expression modal and some first order logic, but by solving the problem of proposition fixation, neural symbols are being applied to solve many problems such as bioinformatics, software verification, and engineering control.



(a) Acc. vs. # pretraining programs (b) Program acc. vs. # programs (c) Acc. vs. # training data

Figure 4 Neural Symbolic has high data efficiency From Yi et al. (2018)

As shown in figure 4 in (Yi et al., 2018), Neuro Symbolic performed better without training than conventional techniques with less data. In other words. It can be seen that data and computing power are used more efficiently than existing technologies. In addition, as shown in Table 1, the accuracy is very high. In particular, it is possible to check the process through which a computer finds an answer in a neural network. Looking at Figure 5, unlike IEP, it is possible to check the process for each process, so it is possible to obtain robust results because it is possible to know in which process the wrong decision is made.

Despite less data and pretraining, similar to existing techniques, higher performance was recorded. As a result of performing Neural Symbolic VQA using the CLEVER dataset in Yi et al. (2018), it showed very efficient data use Figure4. In particular, looking at the results for the different number of question-answer pairs (2K, 9K, and 700K, respectively) in the reinforcement learning stage in (a), even if the number of questions is the same as the standard IEP, the number of programs is small to 100 On the other hand, the existing IEP is less than 40%, while the IEP is less than 40%. When the number of programs is less than 1000, the accuracy converges to almost 100%. As a result of research by dividing the number of annotated programs in (b), the accuracy of 60% of the IEP using the existing 9K was achieved with 270 annotated programs at 1/30 level. Comparing in (c), 270 models were pretrained in advance. However, the number of training questions required to achieve similar performance to the existing model was small.

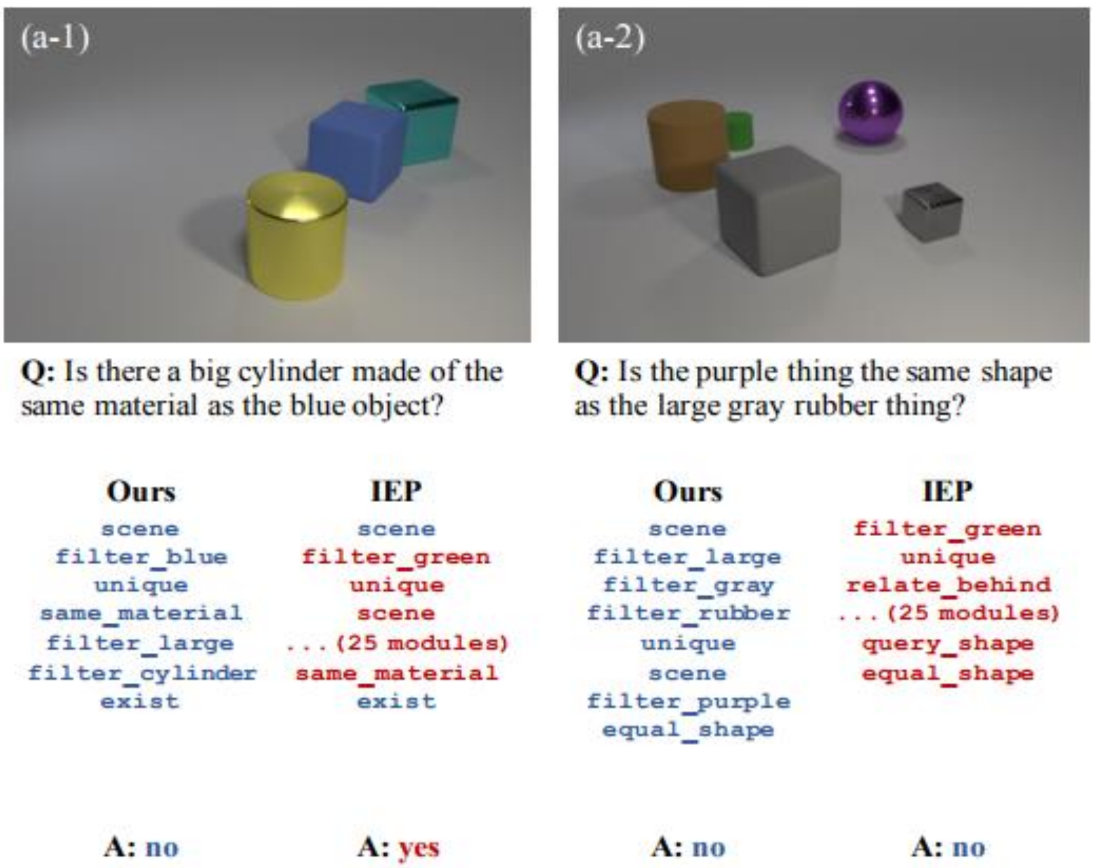


Figure 5 Neural Symbolic Provide Explainable Processing Result Compared to IEP From Yi et al. (2018)

Methods	Count	Exist	Compare Number	Compare Attribute	Query Attribute	Overall
Humans [Johnson et al., 2017b]	86.7	96.6	86.4	96.0	95.0	92.6
CNN+LSTM+SAN [Johnson et al., 2017b]	59.7	77.9	75.1	70.8	80.9	73.2
N2NMN* [Hu et al., 2017]	68.5	85.7	84.9	88.7	90.0	83.7
Dependency Tree [Cao et al., 2018]	81.4	94.2	81.6	97.1	90.5	89.3
CNN+LSTM+RN [Santoro et al., 2017]	90.1	97.8	93.6	97.1	97.9	95.5
IEP* [Johnson et al., 2017b]	92.7	97.1	98.7	98.9	98.1	96.9
CNN+GRU+FiLM [Perez et al., 2018]	94.5	99.2	93.8	99.0	99.2	97.6
DDRprog* [Suarez et al., 2018]	96.5	98.8	98.4	99.0	99.1	98.3
MAC [Hudson and Manning, 2018]	97.1	99.5	99.1	99.5	99.5	98.9
TbD+reg+hres* [Mascharka et al., 2018]	97.6	99.2	99.4	99.6	99.5	99.1
NS-VQA (ours, 90 programs)	64.5	87.4	53.7	77.4	79.7	74.4
NS-VQA (ours, 180 programs)	85.0	92.9	83.4	90.6	92.2	89.5
NS-VQA (ours, 270 programs)	**99.7**	**99.9**	**99.9**	**99.8**	**99.8**	**99.8**

Table 1 High Accuracy in Neural Symbolic AI From Yi et al. (2018)

CHAPTER 3

CURRENT RESEARCH

Even at this time, research in various fields is emerging, and the potential for infinite applications based on these technologies is open. The research introduced in this chapter selects a core research that can be used as a core technology in various fields and upgrade the level of technology based on the research.

There are several types of QA, such as text-based QA, context-based QA that interacts in the context of communication or conversation, knowledge-based QA (KBQA), and vision QA. Among them, knowledge-based answering (KBQA) is a difficult field that requires advanced reasoning such as multi-hop, quantitative, geographical, and temporal reasoning(Cui et al., 2019).

3.1 Logical Neural Network (LNN)

IBM announced that it is possible to design systems with little or no end-to-end training data using Neural Symbolic Question and Answering(NSQA). In the past, thousands of question-and-answer sets were required to create an end-to-end education system, because preparing these data is expensive, labor intensive, and impractical.(Riegel et al., 2020)

They created a system called NSQA to convert a given natural language question into a logical form, and then use LNN, a neural symbol inference technique, to reason and generate answers through a knowledge base. Here, LNN is a logical neural network, a new neuro symbolic technique in which artificial neurons model the concept of weighted real-valued logic. LNN has the advantage that it can be used with domain knowledge for inference because it inherits the main properties of neural networks and symbolic logic in structure.

Let's be a little more specific about LNN. It can model formal logical reasoning by applying recursive computations of truth values moving back and forth. Existing standard neural networks operated only forward, but LNN supports both forward and backward, so it has immunity to incomplete knowledge and complete logical expression. In addition, the real-valued logical form improved the prediction accuracy by expressing the relationship between logical clauses well through neural weights. Another advantage is tolerance for imperfect knowledge. Most AIs use the closed-world assumption to determine false if statements are not in their knowledge base. On the other hand, LNNs can make realistic open-world assumptions by creating upper and lower bounds for each variable and can accommodate imperfect knowledge. Finally, techniques based on Markov logic networks and logic tensor networks are difficult to interpret. Because we have an unknown language structure. Therefore, while it does not perform well in initial learning and inference, LNNs perform well in initial learning and inference.

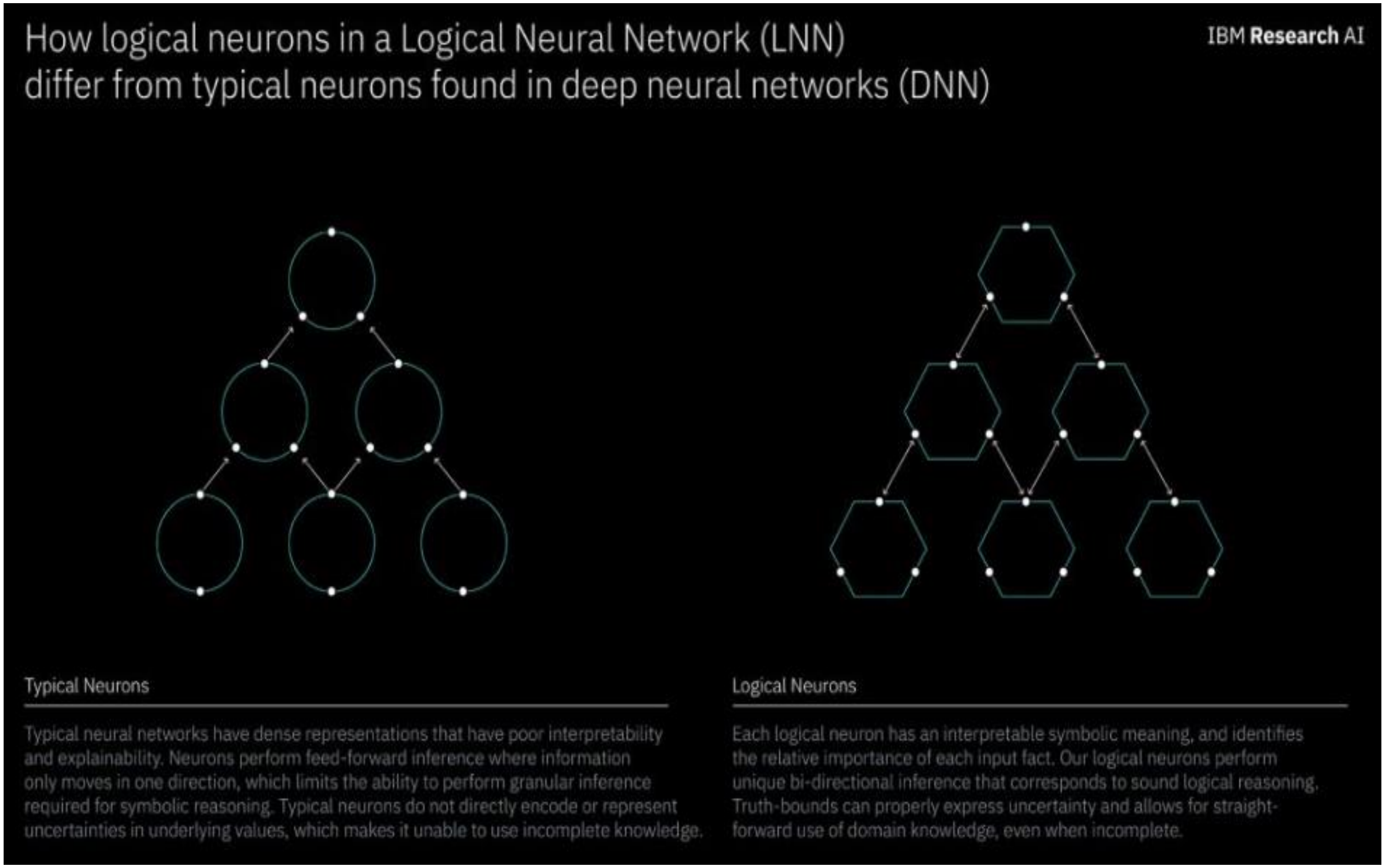


Figure 6 The Difference Between Typical Neurons and Logical Neurons From IBM Research

3.2. Neuro symbolic Concept Learner

It has proven that it can parse visual concepts, words, and sentence semantics without guidance. Simply look at the image, read the question, and derive the answer(Mao et al., 2019). It consists of three modules. After making an object proposal using R-CNN in the Visual Perception part, when an object is displayed in the bound box, it is sent to ResNet-34 to extract region-based and image-based features. It serves to add contextual information to all the screens. This role is essential for inferring relevant properties.

Concept Quantization begins with the premise that visual reasoning requires properties of an object (ex. color, shape, etc.). It is assumed that the features have a visual concept. In Neuro symbolic Concept Learner, the visual feature is a neural operator that connects the object and the space. That is, cubes, spheres, and cylinders are expressed as vectors of shape type.

Domain specific language(DSL) and Semantic Parsing is a semantic parsing module that translates natural language questions into computer-executable programs. DSL deals with a basic set of operations for visual inference, such as filtering objects with a 'sphere' concept or asking properties of those objects. Because DSL operations share input and output interfaces, they can be easily decomposed and combined even in complex problems.

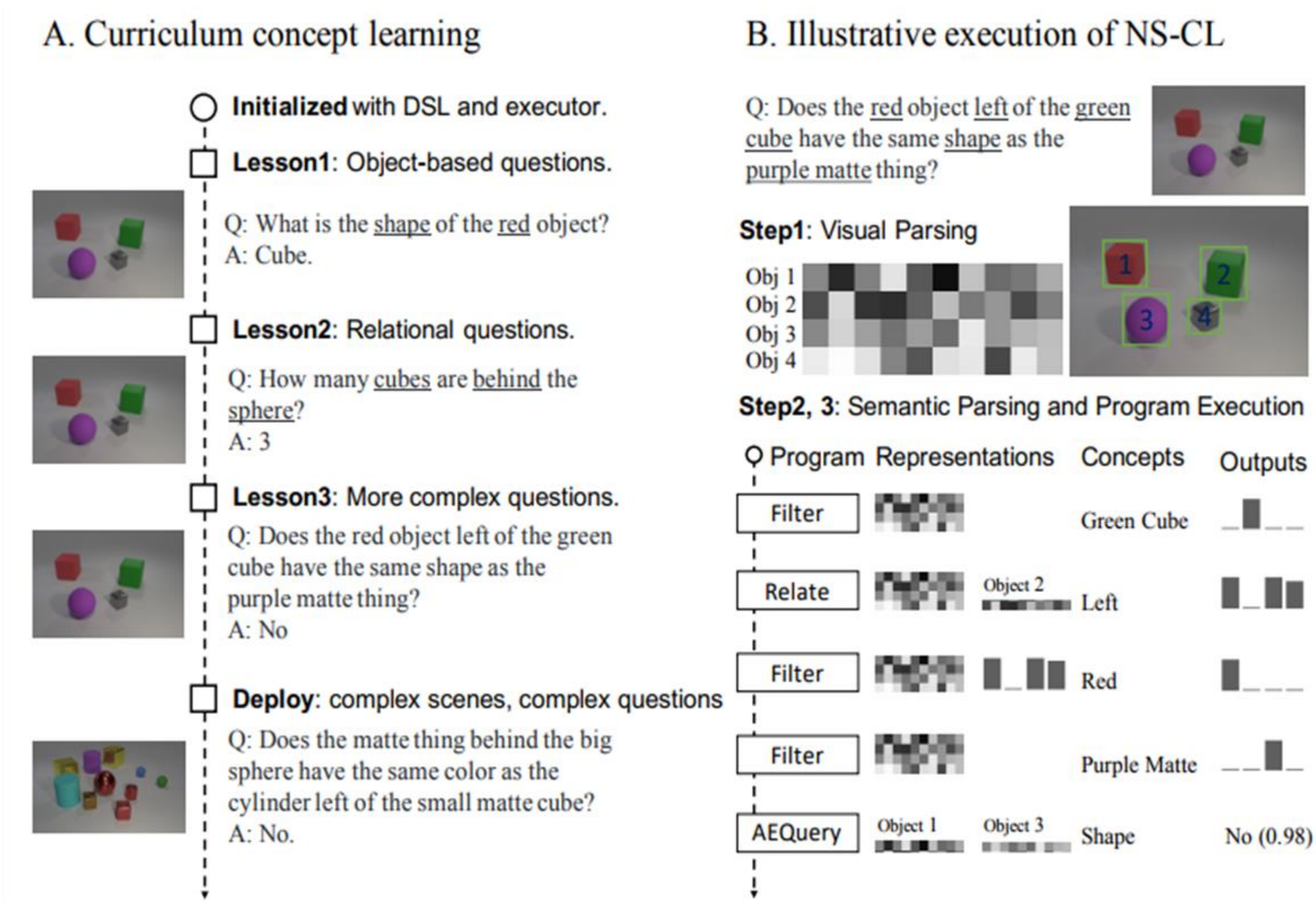


Figure 7 Illustrative Execution Trace of a Neuro Symbolic Concept Learner Program From Mao et al. (2019)

3.3 Meta Concept Learner

Visual Concept-Meta concept Learner (VCML) integrates concept and meta concept learning through images and question-and-answer sets(Han et al., 2020). You can understand that red and green share the same properties of an object, and that spheres and cubes are the same concept. Knowledge of meta concepts will help to overcome the limited, noisy and biased data in existing concept learning. It can learn a superordinate as well as the hypernym that describes synonyms and categories between learning, a word with a broad meaning that more specific words fall under. Meta concepts can help concept learning learn by providing additional supervision at the abstract level: 1) using synonyms to help learn new concepts without additional visual examples (zero shot learning), 2) meta concept You can learn from biased visual data when using the same_kind. For example, you can learn the concept of purple with different hues from 'purple cubes'. 3) Upgrade the data efficiency of overall visual concept learning

In the figure 8, the Visual Meta concept Learner is composed with three modules. (a) a perception module for extracting object-based visual representations. When an image is input, VCML expresses it in an object-based way. It creates object proposals using Mask R-CNN (He et al., 2017), and ResNet-34(He et al., 2015) is used to represent regional-based features of each object. (b) a semantic parsing module for recovering latent programs from natural language question. This program has a hierarchical structure and provides the same_kind filter that can evaluate whether two concepts are the same or not. (c) a neuro-symbolic reasoning module that executes the program to answer the question.

The representation space of the object and the visual concept are combined and expressed as a vector.

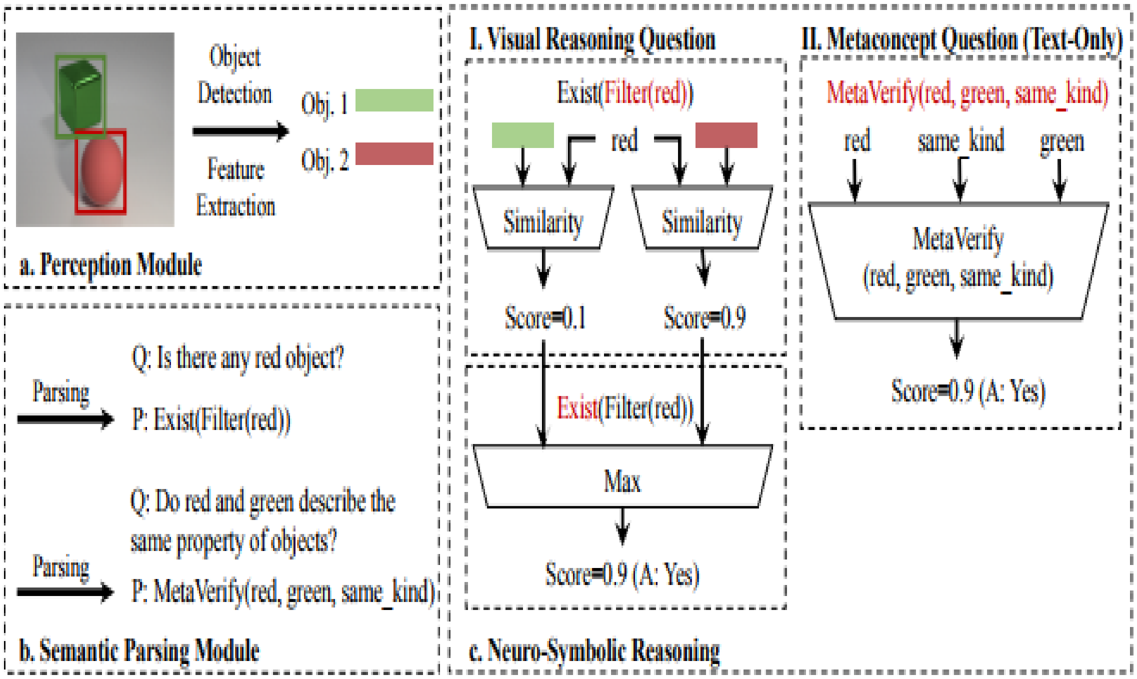


Figure 8 Visual Concept-Meta concept Learner comprised of three modules From Han et al.,(2020)

CHAPTER 4

CHALLENGES

4.1 Challenge by Learning Stage

The challenge facing each stage is to be explained by dividing it into expression, integration, and transfer, which are the processes in which learning and inference take place.(Besold et al., 2017; Garcez et al., 2015)

4.1.1. Representation

Most of the work of neural symbolic learning and reasoning was focused on propositional logic. It is predicted the logic of variable-free representation in early research methods. In neural nets, vectors are used to learn FOL rules. However, these systems could not be used in real life because they were only possible within a limited conceptual and proof setting and were valid only on small samples. In order to overcome these challanegs, special logics such as Description Logic(DL) and Horn Description Logic(HDL), which are methods that consider the logic of intermediate expressions, have been developed, and a method of programming in which the proposition method and the answer are defined using Inductive Logic Programming(Uwents et al., 2011)has been proposed as another method. Through this, the optimal way to express propositional logic well is searched, in particular, recent studies on the integration of DL and rules have shown that the development of DL expression within the Neural Symbolic system has a high potential for development.

The proper answer to the question of variable binding and how a neural network should infer from variables is ‘appropriate representation’. Among the efforts for this, there is extraction of logical expression for representation of expression logic. Examples include logic programs and decision trees. In addition, the main challenge is 'understanding the knowledge expression method in the brain, that is, neuron activation' because the brain causes sub-symbolic behaviors. Since it lacks recent findings, fMRI, and MEG analyzes are studies to overcome these shortcomings(Ganter & Wille, 1999),(Endres et al., 2009). A major future goal is to understand context-influenced meanings, i.e. how semantic construction is done, and the process by which semantics are formed.

4.1.2 Integration

Learning for reasoning makes learning an integral part of the reasoning process. The difficulty of neural symbolic integration is due to the computational complexity of knowledge extraction and the need for a compact representation that can be used based on learning efficient reasoning. To compile the multiple examples about learning episodes, Lifelong Machine Learning(LML) approach is needed(Silver, 2013).

However, in deep networks, modularity is used to find expressions of knowledge, and it is solved by applying connectionist modal logic. It is also expected to reduce the complexity of knowledge extraction through modularity. These methods will be very effective solutions for expressing complexity and will accelerate the development of reasoning.

4.1.3 Transfer

The transfer of knowledge between unrelated domains plays an important role in human learning(Holyoak et al., 2001). 'Inference' is very important in the human learning process, because if the method of applying analogy at the sub-symbol level is implemented in structural learning of the neural sign paradigm, the learning efficiency will increase explosively. Studies have been conducted on how to transmit the insights gained through learning, and the recent trend is that instead of retraining the network model in a new domain, the new trend is to meaningfully transfer the insights gained from the existing network to other networks. However, the next task is 'how to implement the concept of analogical transfer of knowledge level, and how to symbolically express the concept of analogical transfer that occurs between different domains'.

4.2 Limitations of the Presented Studies

All these studies are still only results on a limited data set. In a reality where variables and environmental variables are difficult to control, many limitations and a lot of time and new technologies will be needed to overcome them.

CHAPTER 5

CONCLUSION

70 years after the concept of artificial intelligence appeared, we had to go through two winters. This was due to the misjudgment and excessive expectations of the people of the time that the rosy prospects based on the imagination would be realized in a short time before the accurate understanding of the technology took precedence. And if they couldn't meet those expectations quickly, they had to go through a difficult winter of artificial intelligence every time due to a reduction in research funding and suspension of research support. There is still a long way to go before artificial intelligence that learns on its own and thinks like a human can be applied and put to practical use in real life. Excessive expectations and rosy expectations drawn without a detailed understanding of the research cause greater disappointment to people, and every time limitations and crises are discovered, they make haste and cut off all support. Today, deep learning broke the second winter of artificial intelligence and created a boom in active artificial intelligence research. We need to make sure that the limits of our understanding of technology can be resolved by calmly and publicly speaking. We need to abandon the vague idea that everything will be done in an overly hasty and quick time and that everything will be solved with artificial intelligence, and we need to study with an open mind through various attempts to combine different existing claims, such as Neuro-Symbolic A.I.

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