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Informatics

Deep Learning with Incentives under Constraints

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This paper discusses the main innovations in the field of deep learning methodology, which can have a significant influence on the development of the given field. The modern scientific literature dedicated to the issues of the development of the scope of methodology and certain theoretical approaches are analyzed. There are assumptions about the future trends of the development of deep learning – as a field of applied scientific knowledge – and particularly promising directions are studied in a critical aspect. *© 2023 Bull. Georg. Natl. Acad. Sci.*

deep learning, convolutional neural network, deep self-learning, hybrid model

Artificial Intelligence affects our lives more and more in the last decade. It has a huge impact on society, which continues to grow in the coming years, as expected.

The field of Artificial Intelligence was officially born in 1956 when John McCarthy coined the term and put forward a proposal to consider artificial intelligence as an independent field of research. Today, machine learning and deep learning monopolized artificial intelligence. Deep learning is at the lead of the Artificial intelligence field, but experts share a common opinion, that some changes will be necessary to maintain that leadership.

Systems 1 and 2 in Deep Learning

We should start this issue with a very short description of dual processing model systems 1 and 2.

The theory implies that two forms of thought processes (fast and slow) influence decision-making:

System 1. Fast, intuitive and experiment-based thinking. These are automatic processes that take place unknowingly and unconsciously. They do not require much brain effort (such as computing power and working memory). System 1 uses previous experience and associations formed based on it, including emotions.

System 2. Slow and reflexive thinking. These are controlled processes that rely more on reasoning (logical, analytical). Using reasoning and argumentation is what slows down the system. The Swiss scientist Jean Piaget considers reflective thinking as a process which is carried out by the subject based on the knowledge of logical laws. These laws refer to the connection of the object with the action directed at it, and also to the cognition and awareness of the necessity of such connection.

There is also system 3 in psychology – the subjective reality of a person, in which there is a feeling of the types of perception and signs of the mind formed in the second signalling system;

Yoshua Bengio reported in 2019 on the topic “From deep learning of system 1 to deep learning of system 2” [1].

He gave a description of the current state of deep learning, the distinct tendency of which led to the principle: Let's do everything as big as possible – big data sets, big computers, and big neural networks. He argued that while moving in this direction, we will never reach the next stage of artificial intelligence development.

Bengio uses a dual-system structure from Daniel Kahneman's ideas, which are widely scattered in his most important book “Thinking, Fast and Slow” [2]. Kahneman describes System 1 as a substance that operates “Automatically, quickly, practically without applying force and feeling of voluntary control,” while System 2 allocates attention to the effortful mental activities, which is associated with the subjective experience of agency, choice and concentration.

Rob Taves generalizes the current state of deep learning in his letter [3] published in the American financial and economic magazine Forbes: “Modern advanced systems of artificial intelligence cope with System 1 tasks, but have serious difficulties solving System 2 tasks”. Bengio agrees with this idea. “We invent algorithms, recipes, we can plan, reason, use logic,” he states. These processes are usually very slow compared to what computers do to solve some of these tasks. We would like deep learning to do just such things in the future.”

Bengio confirms [4] that a deep learning system 2 will be able to generalize “Different distributions of data” – what is called coming out from the existing distribution rule, overcoming the limitations of this rule. Currently, deep learning systems have to teach and test uniformly distributed data sets, which answers the hypothesis of data independence and uniform distribution. “We need systems that can handle such changes and keep learning.” A deep learning system 2 will succeed using nonhomogenous data of the real-world.

For this, we will need systems with improved transfer learning capabilities [5]. Bengio suggests, that attention mechanisms and meta-learning – teaching for teaching– represent key components of System 2 cognitive skills.

Deep Learning Based on Neuroscience

Neuroscience is the direction of the science, which is engaged in the study of chemical, biological and anatomical features determining the influence on the work of the brain and nervous system. Neuroscience is an umbrella concept because it combines many interdisciplinary directions, including medicine, chemistry, psychology, molecular biology, anatomy, physics, and others.

Currently, most scientists believe that neuroscience and neurobiology are the same terms, but – according to the Oxford dictionary – these two concepts are defined in different ways:

Neuroscience is the scientific study of the structure and functions of the brain and nervous system;

Neurobiology is a scientific discipline that studies the biology of the nervous system, in particular, the functions indirectly reflecting the behaviour of this system.

Therefore, we will consider neurobiology as one of the directions of neuroscience here.

Using the term *neurology* instead of the concept of neuroscience (which we often encounter, especially in the English literature dealing with artificial intelligence) will also not be entirely correct: While *neuroscience* is engaged with the study of the nervous system, *neurology* is interested in its treatment. Neurology is a branch of medicine that specilises in the central, peripheral, and vegetative nervous systems, and neurologists are doctors who diagnose and treat neurological diseases and disorders.

“Artificial neural network is only a rough analogy of the brain work,” states David Susilo, PhD. in the field of computational neuroscience, from the Google Brain research group. As it is known, the abovementioned group is interested in deep learning of artificial intelligence and has significant achievements in this field.

In the 1950s, several important scientific discoveries laid the foundation for the creation of artificial intelligence. Research in the field of neuroscience has shown that the brain is composed of neural networks that work by the principle of “all-or-nothing”. This conclusion–along with results from cybernetics, information theory, and Alan Turing's theory of computation–pointed to the possibility of the creation of an artificial brain.

Artificial intelligence takes off in the human brain, but modern deep learning doesn't work like that. A convolutional neural network does not work like our vision system. We do not learn based on the labelled data, but rather observe the world. We have combined bottom-up processing with top-down symbolic processing and this is how we realize the cognitive abilities of System 2.

The ultimate goal of artificial intelligence was to create such an electronic brain that could imitate our general-purpose intelligence. Neuroscience can help deep learning advance toward this goal.

One of the most important approaches is neuromorphic computing, which belongs to devices imitating the structure of the brain. As Alberto Romero, an analyst at Cambrian AI Research, wrote in his article [6], “There is a big difference between biological and artificial neural networks: Neurons are information messengers in the brain related to the moments and frequency of jump times, while the strength (voltage) of the signal is constant. Artificial neurons are characterized by completely opposite properties. They are the carriers of the information related only to the power of the input signal, not the time or frequency”. Neuromorphic computing attempts to reduce these differences. In short, neuromorphic computing is a new computer technology which aims to use the principles of the construction and operation of the human brain.

Another defect of artificial neurons is their simplicity.

According to the study [7] published in the magazine „Science”, a group of German scientists proved that “A single neuron can calculate really complex functions; For example, it can recognize objects independently”.

Panayiota Poirazi states that work in her lab aims to understand how dendrites contribute to complex brain functions, such as learning and memory. Dendrites are thin tree-like projections of *non-linear conduction* arising from the body of the neurons, which provide enhanced capabilities of processing, teaching and information storage for neurons. The computational models are constructed and used in the lab that imitates dendritic computations and their influence on cellular and network functions in different brain regions. In close contact with experimental laboratories, Panayiota Poirazzi and her colleagues use behavioural and visualization methods “In vivo” to study the role of dendrites in the behaviour of mice. The Latin term “In vivo” means to conduct an experiment in a living organism on living tissue (or inside living tissue). More importantly, they create algorithms inspired by brain study that take into account the properties of dendrites and aim to improve deep learning tools.

Demis Hassabis, CEO, Chief Executive Officer and co-founder of Deepmind, emphasizes in the article [8] published in the magazine “Neuron” the importance of using neurobiology to ensure the advancement of artificial intelligence. In addition to some of the ideas already mentioned above, two key aspects should be distinguished: intuitive physics and planning. A scientific employee in the company General Electric Research, James R. Kubricht and his colleagues define intuitive physics as follows: “The knowledge underlying the human ability to understand the physical environment and interact with objects and substances that undergo dynamic state changes, making at least approximate predictions about how observed events will unfold."

Deep learning systems can't do this. They are not in the real world, they aren't embodied and they lack the evolutionary baggage that gives us the advantage to navigate our surroundings. Joshua B. Tenenbaum is working on instilling this ability in machines. He is a professor of computational cognitive science at the Massachusetts Institute of Technology and is known for his major contributions to mathematical psychology and Bayesian cognitive science. He was the first in the world to use probabilistic and statistical modelling to analyze the processes of human teaching, reasoning, and perception, and showed how these models could explain a fundamental problem of cognition: How does our mind grasp so much so quickly based on such a small amount of data.

There are many ideas deep learning can take from neuroscience. If we're trying to get closer to intelligence, then why not study the only example we have? As Demis Hassabis states:

"Taking into consideration, that jeopardizing many of the achievements of deep learning is extremely risky, the need for the field of neuroscience and Artificial Intelligence to come together is now more urgent than ever before".

Conclusion

Deep learning systems are extremely useful. In recent years, they have changed the technological landscape, all alone. However, if we wish to create truly intelligent machines, deep learning will need a qualitative renewal – rejection of the principle "the more, the better".

Artificial intelligence is catching up with humans faster and faster, but for development, artificial intelligence needs the efforts of many people in different fields of knowledge.

We do not know which is the best path to achieve truly intelligent systems.

ინფორმატიკა

ღრმა სწავლება წახალისებით შეზღუდვათა პირობებში

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**აკადემიის წევრი, საქართველოს ტექნიკური უნივერსიტეტი, ინფორმატიკისა და მართვის სისტემების ფაკულტეტი, თბილისი, საქართველო*
***საქართველოს ტექნიკური უნივერსიტეტი, ინფორმატიკისა და მართვის სისტემების ფაკულტეტი, თბილისი, საქართველო*

ნაშრომში განხილულია ღრმა სწავლების მეთოდოლოგიის სფეროს ძირითადი ნოვაციები, რომლებსაც შეუძლია მნიშვნელოვანი გავლენის მოხდენა მოცემული დარგის განვითარებაზე. გაანალიზებულია მეთოდოლოგიისა და გარკვეული თეორიული მიდგომების გამოყენების სფეროთა განვითარების საკითხებისადმი მიძღვნილი თანამედროვე სამეცნიერო ლიტერა-ტურა. ჩამოყალიბებულია ვარაუდები ღრმა სწავლების – როგორც სამეცნიერო-გამოყენებითი ცოდნის სფეროს – განვითარების მომავალ ტენდენციებზე და კრიტიკულ ასპექტში შესწავ-ლილია განსაკუთრებით პერსპექტიული მიმართულებები.

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