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Reflections on the Promoting Effect of Quantum Machine Learning on the Development of Artificial Intelligence in the Iteration Process of Machine Learning Technology

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Abstract: With the rapid development of artificial intelligence technology, some shortcomings in the traditional machine learning model have begun to show. With the growth of the quantity of data, too many parameters have become a problem and traditional silicon-based computers are near their physical limits. Quantum machine learning is a new way that will be able to advance the development of artificial intelligence significantly in the future. This paper will introduce and investigate the promoting effect of quantum machine learning on the overall development process of artificial intelligence. By learning about the differences between traditional neural networks and quantum-enhanced algorithms, this paper will show that superposition and entanglement in quantum mechanics can solve computational problems that have been very difficult to solve for a long time. Also, based on the above, it will be explored how quantum feature spaces and quantum neural networks can significantly boost the speed of data processing and pattern recognition. Based on the above results, it is hoped that quantum machine learning will be able to provide a new computing system with enhanced capabilities compared with the current model and thus advance the continuous development of artificial intelligence.

Keywords: Quantum Machine Learning, Artificial Intelligence, Computational Complexity, Algorithm Iteration, Quantum Computing, Neural Networks.

1. Introduction

In the past few decades, the development of artificial intelligence has mainly been driven by continuous iteration in machine learning technology. From the first symbolic logic system and support vector machines to modern deep neural networks and large language models, every stage of the progress in artificial intelligence has been supported by improvements in computing power and algorithms. At present, the development of artificial intelligence is being promoted by many other industries. Modern deep learning architectures have billions or even trillions of parameters and are capable of performing various tasks in natural language processing, computer vision, complex prediction, etc. It is also possible to conclude that computer science has a severe structural issue. At present, the development path of artificial intelligence is constrained by the physical limitations of traditional silicon computers. As Moore's Law will inevitably slow down and the energy consumption for training huge neural networks is getting too high, the old way of just adding more classical processors is no longer economically or technically feasible.

To overcome these basic problems, scientists around the world have begun to pay more attention to quantum computers and are using the excellent features of quantum mechanics, instead of classical binary logic. Quantum machine learning is at the intersection of the two areas mentioned above. Taking advantage of the special characteristics of quantum systems, a new interdisciplinary field has been formed to address problems related to information processing and the execution speed of machine learning algorithms on supercomputers is an issue in traditional computing. Quantum machine learning is not just a theory; it is the next necessary step in the development of artificial intelligence. Researchers have begun to turn difficult optimisation problems and large-scale data matrices into quantum states and are starting to find a way to solve optimisation and other related problems exponentially faster.

This paper studies how well quantum machine learning helps to promote the all-round development of artificial intelligence. In order to solve the problem of slow speed in the original algorithm, a new quantum-improved model has been developed. After the above introduction, Section 2 will examine the history and problems in practice of classical machine learning. Section 3 presents the basic ideas and main functions of quantum machine learning algorithms. Section 4 is about to present some catalytic effects these quantum algorithms will bring to the future development direction of artificial intelligence. Finally, Section 5 is the synthesis of the above, and I hope to offer some new ideas to promote the transformation of modern society. Therefore, both academia and industry have begun to look more closely at the main causes of the present predictive model system. For a long time, the primary way that technology companies in recent years have grown has been to expand data volume, build larger neural networks, add many more graphics processing units, etc., in massive data centers. Although the scaling hypothesis has shown excellent results in the short term for generative models and computer vision, it has also caused serious problems for the ecology and economy. With the development of large-scale artificial intelligence models, so too have their energy consumption and environmental pollution. In addition, there is a high entry barrier for funding, and only a few well-funded enterprises can carry out artificial intelligence research; many other universities and research institutes are lacking. In order to spread good AI and develop in harmony with nature, the basis algorithm for building the system needs to be more energy-efficient than ever before. It is to this end that quantum computers will expand the scope of the entire technology system. Using the laws of quantum mechanics, quantum computers will be able to solve some difficult computational problems more easily.

2. The Iterative Bottlenecks of Classical Machine Learning

Before we can fully appreciate why quantum machine learning is needed, we should first learn about the computation problems in current machine learning. Classical algorithms process information in the form of binary bits and perform linear and matrix algebra operations sequentially or by means of classical parallelization. Although these are very good for the local distribution of data, they have high computational costs and are not practical when the dimension of the data is large. Theoretically, in physics and computer science, for a long time, it has been required that to simulate complex, multi-dimensional probabilistic systems on conventional computers one would need an exponential amount of time and space [1]. Therefore, in recent years, with the application of artificial intelligence to solve problems that were difficult to address through conventional methods, such as the discovery of new drugs and the construction of macroeconomic models, many traditional machine learning models have also reached the end of their performance. There are too many mathematical operations that need to be performed, and the old hardware cannot handle them in time, so the accuracy improvement is relatively small.

In addition, some categories of mathematical problems will never be solved by a traditional machine, even with more hardware. Historically, the development of quantum computing has shown that problems with a large number of possible combinations, such as the discrete logarithm problem and prime factorization, can be solved in polynomial time using quantum mechanics; otherwise, they would take a very long time classically [2]. It was first used for cryptography, but then it was discovered that the optimization landscape of traditional machine learning is a function with a huge number of local minima that can trap the gradient descent algorithm. It is necessary to reduce the high non-convexity of the loss function in deep learning. The old way was to add random noise or increase the number of parameters to address this, but it only concealed the problem by force. Therefore, the current state of traditional artificial intelligence is that it is iterative, and even a small improvement in the algorithm requires a relatively large increase in power consumption and hardware. To break this cycle, we need to move away from traditional binary logic and build algorithms that can handle the complexity of mathematics directly. In terms of the structural defects in old computers, it must be noted that there is an intrinsic constraint on classical memory bandwidth. In recent years, the computation unit of a modern neural network has been idle for a long time, waiting for high-dimensional tensor data to be transferred from physical memory, especially in the Transformer architecture and large convolutional networks. As a result, there is a low iteration speed for the algorithm; this is known as the von Neumann bottleneck. The old engineers have tried to solve this problem by designing very particular Application-Specific Integrated Circuits (ASICs) and elaborate memory hierarchies. These are just engineering band-aids that cannot fix the basic flaws in the architecture. The speed of data transmission in traditional physics and standard electronic circuits is limited by the speed of light. When an artificial intelligence agent tries to learn the specific and numerous relationships in a large amount of data, such as billions of high-definition pictures or many years of world weather records, there is insufficient bandwidth. The size of the algorithm is determined by the quantity of data that needs to be processed; since it cannot be reduced any further, life-saving disease prediction models and autonomous driving have not yet been achieved.

3. Principles and Capabilities of Quantum Machine Learning

Quantum machine learning has introduced quantum bits (qubits) in place of the binary bits of classical computers and uses superposition and entanglement from quantum mechanics. Superposition is used to have one qubit in multiple states at the same time, and thus many computation paths of a quantum algorithm can be explored concurrently. The first reason for the acceleration of the search is inherent quantum parallelism. The first algorithmic development showed that, with the help of quantum mechanical interference to enhance the signal of the correct answer and reduce that of wrong answers, a quadratic speedup could be achieved for searching an unsorted database with many items [3]. It can be applied in machine learning to improve the speed of retrieval and processing for high-dimensional data points and thus reduce the time needed for clustering and pattern recognition in the data.

Entanglement is a form of correlation among qubits that can be far apart. It can handle all of the extensive correlations in the big data well. Quantum principal component analysis can find the structure of a very large density matrix in the problem of dimensionality reduction much faster than any known classical equivalent [4]. A map of the covariance matrix of the data to a quantum state is employed, and an algorithm is used to speed up the exponential extraction of principal eigenvectors. The generalization of the above quantum abilities has provided strong theoretical support for quantum machine learning, and it has been shown that quantum linear algebra routines can theoretically solve systems of linear equations and support vector machines, hidden Markov models, etc., with great speed-ups [5]. In this quantum iteration, the optimisation routine will not take small steps in the data space; instead, it will seek to achieve a good algorithmic result through global optimisation of the quantum state and thus avoid the computation difficulty of traditional deep learning models. The concept of quantum gradients is also a type of parameter update in machine learning models. The first calculation step of classical backpropagation is the computation of the gradient for a loss function using the chain rule in millions of neural network layers. The above process is susceptible to the problem of vanishing gradients; that is to say, during the backpropagation stage of the network, the learning signal will decrease exponentially and fail to reach the deep layers properly. The parameter-shift rule is used in quantum machine learning to obtain gradients of the quantum state. By changing the phase of a quantum gate and executing the quantum circuit, one can obtain the exact analytical gradient efficiently without needing to perform many steps of classical differentiation. This purely quantum mechanical way of looking at it has solved the vanishing gradient problem and now we can quickly and accurately optimise very complex, multi-layered quantum circuits. Therefore, the training period of the artificial intelligence model will no longer be a slow and error-prone classical calculation; instead, it will be an elegant and highly stable physical measurement process that can reach the global algorithmic minimum much more quickly.

4. The Promoting Effect of QML on Artificial Intelligence

The introduction of quantum mechanics to algorithm design is a big push for the development of artificial intelligence in recent years. According to recent research in the quantum field, quantum technology will not only be used to speed up calculations but also create new ways of learning that are impossible for classical computers to realise [6]. The other is that the dimension of the feature space is enlarged to some extent. Traditionally, kernel methods have been used in machine learning to increase the dimension of data and then perform a simple classification. Quantum computers can be used for quantum enhancement to map classical data into a high-dimensional feature space, and with the help of entangled states, classification problems that are difficult to solve with classical computers can also be addressed [7]. It can expand the scope of pattern recognition for artificial intelligence to help it analyse various data, such as people's genetic information and changes in the economy of the world.

Based on the above theory, programmable superconducting processors have been used to achieve quantum supremacy in practice, and they can perform some sampling tasks many times faster than conventional simulators [8]. It can be used to promote the development of artificial intelligence by demonstrating that complex, random quantum circuits can be operated and measured reliably. Given the hardware stability mentioned above, some scholars have constructed quantum neural networks. Based on the above mathematical analysis, it can be seen that these quantum neural networks have relatively high effective capacity and expressiveness compared with traditional neural networks of the same size [9]. They can be a simple form of a function and can also exhibit relationships between different items in data.

In fact, this round has also shown some success in the processing of data by means of quantum machine learning. The strength of data in quantum machine learning is that, even with a relatively small number of data points and noise, quantum algorithms can still learn some useful predictive models that classical systems cannot recognise due to the size of the data [10]. Therefore, there is little data dependency in modern artificial intelligence. Quantum machine learning can be used to learn from a small number of data points with high accuracy, and it is well-suited to the problem of high-dimensional feature space; thus, this technology will provide new support for the development of artificial intelligence beyond the limits of classical computing and start a new era of strong data analysis.

5. Conclusion

The development of artificial intelligence in recent years has been in line with changes in computer technology. However, since traditional machine learning models have reached the hardware limits of silicon chips and face problems in mathematics, we must change our way of thinking. This paper has been exploring how the powerful new technologies of quantum machine learning will drive the future development of artificial intelligence. Quantum mechanics has left behind the old sequential and binary computation model, so fast parallel processing and optimisation have been developed to help us explore the large space of features for artificial intelligence algorithms more efficiently.

It can be seen that quantum machine learning has addressed many problems in deep learning. Quantum algorithms can address the problem of non-convex loss functions by avoiding a large number of calculations with the help of superposition and entanglement to reduce the dimensionality of large datasets efficiently. With the beginning of quantum neural networks, it is hoped that in the future, artificial intelligence systems will need fewer parameters and smaller datasets to achieve good prediction performance. Thus, the foundation of the economy of artificial intelligence development will be modified; it will no longer be driven by raw data but rather by elegant algorithms.

In short, quantum machine learning is not an addition to the current software; it is a whole new kind of thinking. Although there are still many technical problems in the stability and error correction of quantum hardware, some results have already been achieved in theory and practice. With the development of quantum computers, they will be applied to solve problems in artificial intelligence and related fields. If artificial intelligence is to help address the difficult scientific and engineering problems of human civilization, then in the long run, it will be necessary to constantly integrate and improve quantum machine learning.

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