

Overview of Efficient Numerical Computing Methods Based on Deep Learning

Kejun Yang*

China Jiliang University, Hangzhou 310018, Zhejiang, China

*Corresponding author: Kejun Yang, 2402343218@qq.com

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Abstract: This article reviews the application and progress of deep learning in efficient numerical computing methods. Deep learning, as an important branch of machine learning, provides new ideas for numerical computation by constructing multi-layer neural networks to simulate the learning process of the human brain. The article explores the application of deep learning in solving partial differential equations, optimizing problems, and data-driven modeling, and analyzes its advantages in computational efficiency, accuracy, and adaptability. At the same time, this article also points out the challenges faced by deep learning numerical computation methods in terms of computational efficiency, interpretability, and generalization ability, and proposes strategies and future development directions for integrating with traditional numerical methods.

Keywords: Deep learning; Efficient numerical value; Method of calculation

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1. Introduction

With the rapid development of big data and artificial intelligence, deep learning, as an important branch of machine learning, has demonstrated strong application potential in many fields. Numerical computation, as a fundamental tool in scientific research and engineering practice, directly affects the efficiency and accuracy of problem-solving. Introducing deep learning into the field of numerical computing not only provides new ideas for traditional numerical methods but also has the potential to solve some difficult problems that traditional methods find difficult to overcome. Therefore, exploring efficient numerical computation methods based on deep learning is of great significance, as it will bring new opportunities and challenges to scientific computing and engineering applications.

2. Overview of the fundamentals and applications of deep learning in numerical computing

2.1. The basic principles and framework of deep learning

Deep learning, as an important branch of machine learning, focuses on simulating the learning process of the

human brain by constructing multi-layer neural networks. A neural network consists of an input layer, a hidden layer, and an output layer, each layer containing multiple neurons connected by weights and biases. The activation function plays a non-linear transformation role in neural networks, enabling the network to fit complex functional relationships. The loss function is used to measure the difference between the predicted value and the true value of the model, while the optimization algorithm minimizes the loss function by continuously adjusting weights and biases, to train an accurate model as shown in **Figure 1** ^[1].

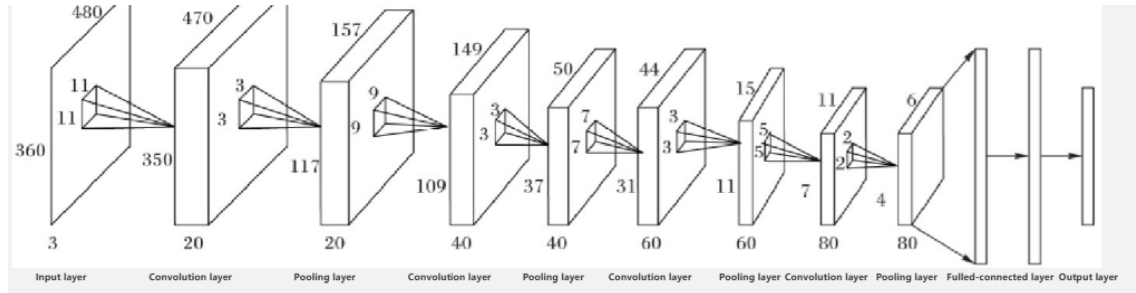


Figure 1. Convolutional neural network

Currently, deep learning frameworks such as TensorFlow and PyTorch have become the preferred tools for researchers and engineers. These frameworks provide rich APIs and flexible computational graph mechanisms, making deep learning implementation more efficient and convenient.

2.2. Traditional methods and challenges of numerical computation

Numerical computation is a fundamental tool in scientific research and engineering practice, and traditional methods such as finite difference, finite element, and spectral methods have achieved significant results in practical applications. However, these methods face many challenges when dealing with high-dimensional and nonlinear problems. Although the finite difference method is simple and easy to understand, it is more difficult to handle complex boundary conditions and irregular regions; Although the finite element method applies to various complex-shaped regions, it requires a large amount of computation and has low efficiency in solving highly nonlinear problems; Although spectral methods have high accuracy, they require functions to have sufficient smoothness and are cumbersome for handling nonperiodic boundary conditions as shown in **Figure 2** ^[2].

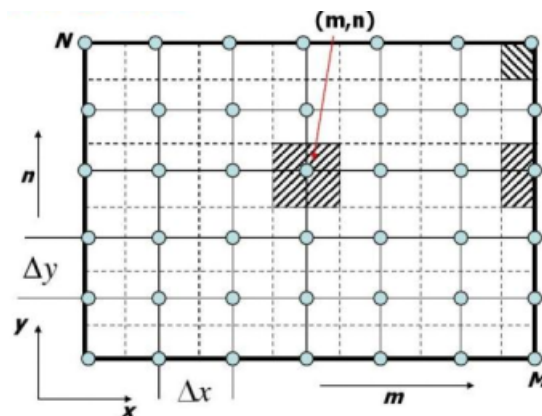


Figure 2. Finite difference method

2.3. The application prospects of deep learning in numerical computing

Deep learning has shown great potential in the field of numerical computing. In solving partial differential equations, deep learning can approximate the true solution by learning solutions that satisfy the equation and boundary conditions, thus overcoming the limitations of traditional methods in solving complex equations. In terms of optimization problems, deep learning can utilize its powerful function-fitting ability to find optimal or approximate optimal solutions, improving solving efficiency [3]. In addition, deep learning can also be combined with data-driven modeling to improve the accuracy of numerical predictions by integrating observational data and physical models. These application examples fully demonstrate the broad prospects and enormous potential of deep learning in numerical computing.

3. The application of deep learning in solving partial differential equations

3.1. The principle of using deep neural networks to solve partial differential equations

Deep neural networks, especially Physical Information Neural Networks (PINNs), provide a novel and effective method for directly solving partial differential equations. PINNs directly embed the physical laws, boundary conditions, and initial conditions of partial differential equations into the loss function of neural networks. During the training process, the neural network continuously adjusts its parameters through learning to minimize the loss function and approximate solutions that satisfy the equation and boundary conditions as shown in **Figure 3**.

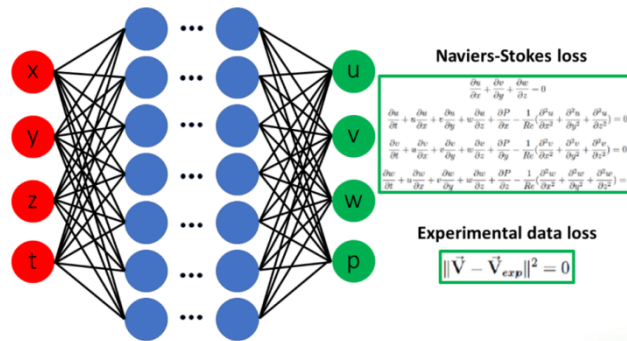


Figure 3. Physical information neural network

PINNs use automatic differentiation techniques to calculate the derivatives of neural network outputs concerning input variables, which are used to construct residual terms for partial differential equations. By minimizing the sum of squared residuals (i.e. loss function), the neural network gradually learns solutions that satisfy the equation and boundary conditions. This method avoids the grid partitioning and discretization process in traditional numerical methods and has higher flexibility and adaptability [4].

3.2. Deep learning for solving fluid dynamics problems

The Navier-Stokes equations in fluid dynamics problems are a typical class of partial differential equations, and their solution is of great significance for understanding the laws of fluid motion. Traditional numerical methods such as finite element and finite difference methods face problems such as high computational complexity and grid dependence when solving Navier-Stokes equations. Deep learning, especially PINNs, provides new ideas for solving such problems as shown in **Figure 4**.

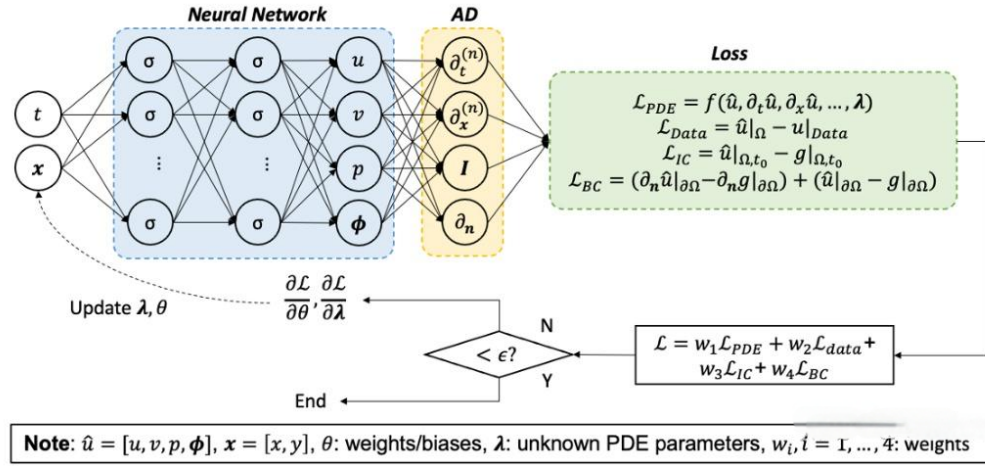


Figure 4. Solving fluid dynamics equations with neural networks

Studies have shown that by constructing appropriate neural network structures and embedding physical information from Navier-Stokes equations, PINNs can accurately predict the velocity and pressure fields of fluid flow. Compared with traditional numerical methods, PINNs have significant advantages in computational efficiency, especially in complex scenarios such as high Reynolds number flows. In addition, PINNs can also handle problems with irregular boundaries and complex geometric shapes, further expanding their application scope.

3.3. The application of deep learning in the inverse problem of partial differential equations

The inverse problem of partial differential equations is an important class of problems in scientific research and engineering practice, such as parameter identification, source term inversion, etc. This type of problem is typically ill-posedness, meaning that the existence, uniqueness, and stability of the solution are difficult to guarantee. Traditional methods often face many difficulties when dealing with such problems.

Deep learning, especially combined with PINNs, provides a new approach for solving inverse problems of partial differential equations. By constructing a neural network containing the parameters to be solved and embedding the physical information of the inverse problem into the loss function, the neural network can gradually learn solutions that satisfy the conditions of the inverse problem during the training process. This method can not only effectively handle the ill-posedness in inverse problems, but also improve the accuracy and efficiency of the solution. For example, in parameter identification problems, PINNs can accurately identify unknown parameters in partial differential equations, providing accurate basic data for subsequent numerical simulations and predictions^[5].

4. Efficient algorithm of deep learning in optimization problems

4.1. The foundation of deep learning optimization algorithms

In deep learning, optimization algorithms are key to training neural networks. Gradient descent is one of the most fundamental optimization algorithms, which calculates the gradient of the loss function and updates the network parameters in the opposite direction of the gradient to minimize the loss function. However, gradient descent may face problems such as slow convergence speed and getting stuck in local optima when solving large-scale

optimization problems.

To overcome these limitations, researchers have proposed various improved optimization algorithms, such as the Adam algorithm. The Adam algorithm combines the advantages of the momentum method and the RMSprop method and dynamically adjusts the learning rate to accelerate convergence speed and improve stability. When solving large-scale optimization problems, improved optimization algorithms such as Adam's algorithm usually perform better than traditional gradient descent methods^[6].

4.2. The application of deep learning in combinatorial optimization problems

The combinatorial optimization problem is an important type of optimization problem, such as the traveling salesman problem, backpack problem, etc. This type of problem usually has a discrete solution space, and the number of solutions increases exponentially with the size of the problem, so traditional methods are often difficult to solve.

Deep learning provides new solutions for combinatorial optimization problems. By constructing an appropriate neural network structure and embedding the constraints and objective functions of combinatorial optimization problems into the loss function of the neural network, deep learning can gradually learn solutions that satisfy the problem conditions during the training process. For example, in the traveling salesman problem, deep learning can find the optimal or approximately optimal travel path by learning the distance relationships between cities and the patterns of travel routes^[7]. In the backpack problem, deep learning can determine the optimal item selection plan by learning the relationship between the value and weight of items.

4.3. The practice of deep learning in function optimization

Function optimization problems are another important type of optimization problem, especially nonlinear function optimization problems. Traditional methods often face challenges such as complex function landscapes, slow convergence speed, and susceptibility to local optima when dealing with such problems.

Deep learning, through its powerful function-fitting ability, can learn the features of function landscapes, thereby accelerating convergence to the global optimal solution. For example, when solving complex nonlinear function optimization problems, a deep neural network can be constructed to approximate the objective function, and the gradient information of the neural network can be used to guide the optimization process. By continuously learning the changing patterns of the function landscape, deep learning can gradually adjust the optimization direction, avoid falling into local optima, and accelerate convergence to the global optimum. This practice has achieved significant results in multiple fields, demonstrating the enormous potential of deep learning in function optimization problems.

5. Data-driven deep learning numerical computation methods

5.1. Basic principles of data-driven modeling

Data-driven modeling is a method of constructing and training numerical models based on large amounts of data. Unlike traditional methods that rely on physical laws and mathematical equations for modeling, data-driven modeling mainly relies on statistical patterns and pattern recognition of data. In deep learning, this is typically achieved by building deep neural networks and training them using large amounts of data. These networks are capable of automatically extracting features from data and learning complex mapping relationships behind the data^[8].

Compared to traditional physical models, data-driven models are more flexible and able to adapt to more

complex and changing environments. However, they also depend on the quality, and quantity of data, and may lack physical interpretability. However, data-driven models and physical models are not completely opposed, and the two can be integrated to leverage their respective strengths.

5.2. The application of deep learning in data assimilation

Data assimilation is a technique that combines observational data with physical models to improve the accuracy of numerical predictions. Deep learning plays an important role in data assimilation. By constructing deep neural networks, observation data can be integrated into the prediction process of physical models, thereby correcting the initial conditions or parameters of the model and improving the accuracy of predictions as shown in **Figure 5**.

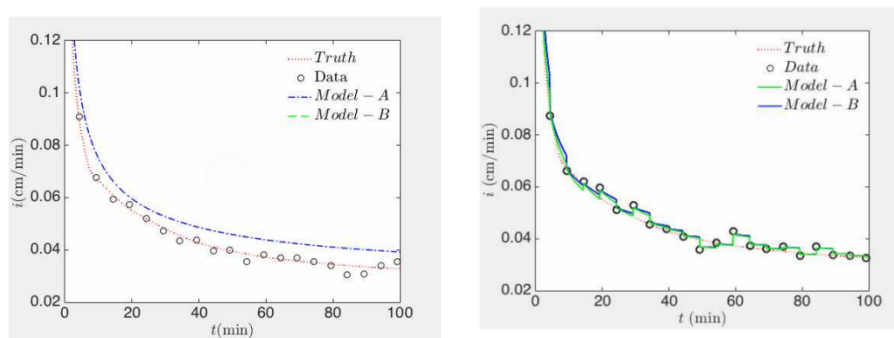


Figure 5. Data assimilation

Data assimilation techniques have been widely applied in fields such as meteorological forecasting and ocean simulation. For example, in meteorological forecasting, deep learning can integrate satellite observation data, ground observation station data, and meteorological models to provide more accurate weather forecasts. In ocean simulation, deep learning can integrate buoy data, satellite remote sensing data, and ocean circulation models to improve the accuracy of ocean state prediction.

5.3. Practice of data-driven deep learning in uncertainty quantification

Uncertainty, such as randomness and fuzziness, often accompanies numerical calculations. Deep learning has shown great potential in dealing with these uncertain problems. By constructing appropriate neural network structures, deep learning can estimate the uncertainty of prediction results and provide confidence intervals or probability distributions ^[3].

For example, in financial risk assessment, deep learning can estimate the uncertainty of investment returns, providing decision-makers with risk assessment and decision support. In environmental science, deep learning can estimate the uncertainty of pollutant concentration prediction and provide a scientific basis for environmental policy formulation. These practices indicate that data-driven deep learning has broad application prospects in uncertainty quantification.

6. Challenges and future prospects of deep learning numerical computing methods

6.1. Current challenges in deep learning numerical computation methods

Although deep learning has shown great potential in the field of numerical computing, it still faces many challenges. Firstly, computational efficiency is a prominent issue. Deep learning models, especially deep neural

networks, typically require a significant amount of computational resources and time to train, which is particularly evident when dealing with large-scale numerical computing problems. Secondly, the lack of interpretability is also a major drawback of deep learning numerical computation methods. Deep learning models are often seen as ‘black boxes’, and their decision-making processes lack clear physical or mathematical explanations, which limits their application in certain fields that require interpretability. Finally, generalization ability is also a concern for deep learning numerical computation methods. Although deep learning performs well on training data, its performance may significantly decrease when faced with unseen data ^[9].

These challenges have had a profound impact on the development of deep learning numerical computation methods. The issue of computational efficiency limits the application of deep learning in real-time or large-scale numerical computing; Insufficient interpretability hinders the promotion of deep learning in certain fields; The issue of generalization ability requires researchers to pay more attention to the generalization performance and robustness of the model.

6.2. Fusion strategy of deep learning and other numerical methods

To overcome the challenges of deep learning numerical computation methods, researchers have begun to explore ways to integrate deep learning with traditional numerical methods. For example, deep learning models can be combined with traditional numerical methods such as finite element and finite difference, utilizing the powerful learning ability of deep learning to improve the computational efficiency and accuracy of traditional methods.

In specific cases, this fusion method has demonstrated significant advantages. For example, in fluid dynamics simulations, introducing deep learning models to accelerate the solving process can significantly improve computational efficiency; In solid mechanics analysis, using deep learning models to optimize the generation of finite element meshes can improve computational accuracy ^[10]. These practices indicate that the integration of deep learning and traditional numerical methods is an effective way to improve numerical computing performance.

6.3. Future prospects of deep learning numerical computation methods

Looking ahead to the future, the development of deep learning in the field of numerical computing will show the following trends: firstly, computational efficiency will continue to improve. Through algorithm optimization and hardware acceleration, the computational efficiency of deep learning numerical computing methods will be significantly improved; Secondly, interpretability will gradually increase, and researchers will strive to develop more interpretable deep learning models to meet the demand for interpretability in certain fields; Thirdly, the generalization ability will receive more attention, and researchers will place greater emphasis on the model’s generalization performance and robustness to improve the practicality of deep learning numerical computation methods ^[11].

To promote the development of deep learning numerical computing methods, it is recommended to strengthen interdisciplinary cooperation and promote the deep integration of deep learning and traditional numerical methods; At the same time, research and development investment should be increased to support the application and promotion of deep learning numerical computing methods in more fields.

7. Conclusion

Deep learning has shown great potential in the field of numerical computing, bringing innovation to traditional numerical methods. Despite facing challenges such as computational efficiency, interpretability,

and generalization ability, the application prospects of deep learning numerical computing methods are broad through the integration with traditional numerical methods and optimization of algorithms and hardware. In the future, with the continuous advancement of technology, deep learning will play an important role in more scientific computing and engineering applications, providing efficient and accurate solutions for solving complex problems.

Disclosure statement

The author declares no conflict of interest.

References

- [1] Liu D, Chen Q, Wang X, 2024, Deep Learning Method for Solving Linear Integral Equations with Primitive Function Transformation. *Computational Physics*, 41(5): 651–662.
- [2] Li Q, Zhu R, Li S, et al., 2024, Overview of Numerical Calculation Methods for Electrothermal Coupling of Converter Transformers. *High Voltage Technology*, 50(10): 4734–4748.
- [3] Niu Q, Dong S, 2023, Research on Numerical Calculation Method of Infrared Radiation from Rocket Engine Spray Flames (Invited). *Optoelectronic Technology Application*, 38(1): 1–10.[4] Hu J, Zhu H, Huang X, et al, 2024, Forest Mobile Robot Tree Trunk Detection based on Deep Learning. *Forest Engineering*, 40(4): 109–114.
- [5] Yin H, Nan Z, 2024, Investor Sentiment Mining based on Deep Learning and its Impact on Stock Price Collapse Risk. *Journal of Central University of Finance and Economics*, (3): 36–56.[6] Zhang H, Zhang H, 2022, Research on the Prediction Method of Effective Proliferation Factor of Core Based on Convolutional Neural Network Model. *Modern Applied Physics*, 13(2): 6.
- [7] Yang C, 2021, Review on Theoretical Model and Numerical Methods of Hydraulic Fracturing. *Yunnan Chemical Industry*, 48(1): 17–20.[8] Li X, Zhang P, Chen G, et al., 2019, The Rising Behavior of Bubbles and Interfacial Mass Transfer in Liquid: Experimental Study and Numerical Simulation. *Advances in Chemical Engineering*, 38(2): 740–751.
- [9] Dinsmore D, Alexander P, 2012, A Critical Discussion of Deep and Surface Processing: What It Means, How It Is Measured, the Role of Context, and Model Specification. *Educational Psychology Review*, (24): 499–567.
- [10] Chang Z, Martin V, Tammy S, 2009, A Cross-cultural Study of Online Collaborative Learning. *Multicultural Education & Technology Journal*, 3(1): 33–46.
- [11] Gerry G, Desiree J, Paul A. Kirschner, 2016, Changing Learning Behavior: Self-efficacy and Goal Orientation in PBL Groups in Higher Education. *International Journal of Educational Research*, 75: 146–158.

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