Guest Editorial

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Evolutionary Neural Architecture Search and Applications

Deep neural networks (DNNs) have shown significantly promising performance in addressing real-world problems, such as image recognition, natural language processing and self-driving. The achievements of DNNs owe largely to their deep architectures. However, designing an optimal deep architecture for a particular problem requires rich domain knowledge on both the investigated data and the neural network domains, which is not necessarily held by the end-users. Neural architecture search (NAS), as an emerging technique to automatically design the optimal deep architectures without requiring such expertise, is drawing increasing attention from industry and academia. However, NAS is theoretically a non-convex and non-differentiable optimization problem, and existing methods are incapable of well addressing it. Evolutionary computation approaches, particularly genetic algorithms, particle swarm optimization and genetic programming, have shown superiority in addressing real-world problems due largely to their powerful abilities in searching for global optima, dealing with non-convex/non-differentiable problems, and requiring no rich domain knowledge. In this regard, deep neural architecture designed by evolutionary computation approaches, so called evolutionary neural architecture search (ENAS), have attracted the interest of many researchers.

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This special issue has brought together researchers to report state-of-the-art contributions on the latest research and development, up-to-date issues, challenges, and applications in the field of ENAS. Following a rigorous peer review process, five papers have been accepted for publication in this special issue.

The first paper included in the special issue is entitled "Evolutionary Multi-Objective Model Compression for Deep Neural Networks" authored by Z. Wang et al., which aims at accelerating the inference speed of DNNs by optimizing the model size and accuracy simultaneously with evolutionary algorithms. The architecture population evolution was employed to explore and exploit the network space of pruning and quantization. In addition, a two-stage co-optimizing strategy of pruning and quantization was proposed to significantly reduce time cost during the architecture search process. To further lower energy consumption and reduce the model size, various dataflow designs and parameter coding schemes were also considered in the optimization process. Unlike most related research solely focusing on reducing the model size while maintaining the model accuracy, the work in this paper can achieve a trade-off between different model sizes and model accuracies, which meets the requirements for most edge devices in real-world scenarios. The experimental results demonstrated that the proposed algorithm can obtain a broad range of compact DNNs for diverse memory usage and energy consumption requirements.

The second paper, titled "Fast and Unsupervised Neural Architecture Evolution for Visual Representation Learning" by S. Xue et al., proposes the FaUNAE algorithm to improve the unsupervised visual representation learning ability against the supervised peer competitors. Specifically, FaUNAE employed the evolutionary algorithm to search for promising neural architectures from an existing architecture designed by experts or existing NAS algorithms that focus on the transferability from a small dataset to a larger dataset. To reduce the search cost and enhance the search efficiency, the prior knowledge and the inferior, as well as least promising operations, were used during the evolutionary process. In addition, the contrast-loss function was utilized as the evaluation metric in a student-teacher framework to achieve the self-supervised evolution. FaUNAE was evaluated on four widely used large-scale benchmark datasets. The results demonstrated the effectiveness of FaUNAE upon various downstream applications, including object recognition, object detection, and instance segmentation.

The third paper entitled "Self-Supervised Representation Learning for Evolutionary Neural Architecture Search" by C. Wei et al. proposes a novel performance predictor, aiming to enhance the efficiency of ENAS algorithms. Specifically, the ENAS algorithms are often computationally expensive in practice because hundreds of DNNs needed to be trained during the search process. Performance preceptors are a kind of regression model that can directly predict the performance of a neural network without any training and is a hot research topic among the community. However, the training of performance predictors requires a large number of well-trained neural networks, which is often scarce in practice. To address this issue, this paper first developed a new encoding strategy of architectures for calculating the graph edit distances among different architectures. Also, two self-supervised learning methods were designed to improve the prediction performance by learning the meaningful representations of neural architectures. This can help to enhance the quality of the training data fed to the performance predictors. The experiments demonstrated promising performance of the proposed performance predictor against the peer competitors. In addition, the proposed performance predictor is integrated into an ENAS algorithm for validation, and the results also showed its superiority of searching for promising neural architectures.

In the fourth paper, "Forecasting Wind Speed Time Series Via Dendritic Neural Regression" by J. Ji et al., proposes a regressive version of the dendritic neuron model (DNM), i.e., dendritic neural regression (DNR), to forecast wind power. Particularly, wind energy is one of the fastest-growing green energy resources. Precise forecasting wind power is crucial in planning the power system and operating the wind farm. However, since the wind speed time series is with chaotic properties and high volatility, traditional methods are incapable of producing satisfactory forecasts. DNM is a plausible biological neural model and has the potential to forecast wind power well. However, DNM is originally designed for classification problems. To this end, DNR is developed based on DNM to forecast the wind power that is a regression task. Like other neural network-based models, the performance of DNR is also voluntary to its architecture design. To address this problem, the states of matter search (SMS) algorithm is used to search for the promising architecture of DNR without much manual effort. The experiments were conducted on two benchmark datasets with two different time intervals. The results revealed that DNR can provide superior performance compared to its competitors, and DNR-SMS was an efficient tool for wind speed prediction.

The fifth paper, "A Self-Adaptive Mutation Neural Architecture Search Algorithm Based on Blocks" by Y. Xue et al., proposes the algorithm named SaMuNet to tackle the problem of "loss of experience" caused by ENAS algorithms in their early search stage. Specifically, most of the existing ENAS algorithms mainly focused on investigating the search space or evaluation strategy to enhance their performance. However, the search strategy also plays an important role during the whole process. In addition, the information of individuals in different generations are also crucial to the performance of the corresponding evolutionary algorithm, which is ignored by most existing ENAS algorithms. To address both issues, SaMuNet incorporated a self-adaptive mutation component into the framework of the evolutionary algorithm to effectively search for the neural architectures. Furthermore, a semi-complete binary competition selection strategy was also designed into SaMuNet to prevent population degradation and slow convergence. In addition, motivated by the recent advances of DNN models, the building blocks of DenseNet and ResNet were also designed as the search units of SaMuNet. The performance of SaMuNet was compared with 17 peer competitors on CIFAR10 and CIFAR100 benchmark datasets. The results demonstrated that SaMuNet can outperform most of them in terms of both the classification accuracy and the consumed computational resource.

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