A Survey on Deep Learning-based Resource Allocation Schemes

Donghyeon Kim*, Haejoon Jung*, and In-Ho Lee†

* Department of Electronics and Information Convergence Engineering, Kyung Hee University, Yongin-si, 17104, South Korea
† School of Electronic and Electrical Engineering Hankyong National University, Anseong 17579, South Korea
Emails: {dhkim3988, haejoonjung}@khu.ac.kr and ihlee@hknu.ac.kr

***Abstract*—The growing number of complex and heterogeneous nodes and base station applications has required a high computational complexity to handle wireless resources. To tackle this problem, deep learning-based resource allocation schemes have emerged to alleviate the excessive overhead issue of conventional iterative algorithms. Specifically, the deep learning technique is primarily divided into three types: supervised learning, unsupervised, and reinforcement learning. In this paper, we review the deep learning-based resource allocation schemes based on the aforementioned training methods, and the limitations and technical challenges in the future are addressed.**

***Index Terms*—Deep learning, machine learning, resource allocation**

I. Introduction

The deep learning technique is attracting significant attention from both academia and industry for its capability to process a significant amount of highly complex data. In deep learning, the training procedure can learn to determine suitable weight values between neural nodes, by which the system performances can be considerably improved in various applications such as voice and image recognition, language interpretation, and semantic analysis [1]. Meanwhile, due to such superiority, the deep learning technique is also widely used in wireless networks, which inherently yield high-complexity and ultra-dense deployment, as in [2]. In particular, to avoid the huge computational complexity of the conventional iterative algorithms for radio resource allocation, diverse machine learning algorithms are proposed in wireless networks [3]–[6].

Because of its effectiveness in practical systems, the deep learning technique is broadly used in resource management [7]. Specifically, deep learning-based resource allocation schemes include user association, subchannel allocation, beamforming, and power allocation, etc. In this context, we review the existing studies on deep learning-based resource allocation schemes, which provide tremendous effectiveness to handle complex and intertwined wireless resources. Moreover, we discuss open research problems of applying deep learning in practical systems and present several insights into future research directions.

II. Deep Learning-based Resource Allocation Schemes

In this section, we investigate the deep learning-enabled resource allocation schemes which focus on three types of machine learning algorithms: supervised, unsupervised learning, and reinforcement learning. First, the supervised learning-based resource allocation schemes, which are trained and approximated to the optimal labeled data, are proposed to overcome the limitations of conventional iterative algorithms [8], [9]. In [8], the authors propose a power allocation scheme with a supervised deep learning approach in the backscatter-aided vehicular networks, where they show similar performance results to the optimal. Similarly, the power allocation scheme is studied in the multi-carrier non-orthogonal multiple access with simultaneous wireless information and power transfer systems [9]. In these studies, it is demonstrated that supervised learning can clearly achieve similar performance to the optimal one with significantly low complexity.

In contrast to supervised learning, deep reinforcement learning (DRL) can train the agent in a way that it selects the optimal action corresponding to the highest reward for a given environment state. Thus, DRL-based resource allocation schemes such as deep Q-network (DQN) and deep deterministic policy gradient (DDPG)-based algorithms are proposed, as in [10], [11]. The authors in [10] propose a DQN-based unmanned aerial vehicle (UAV) base station deployment scheme for providing energy-efficient services to ground users. Also, the DDPG-based flight resource allocation framework is proposed in the UAV-assisted sensor network [11]. Moreover, the DRL methods are used for resource allocation algorithms in systems with multiple diverse requirements, as in [12]–[14], because of the capability to approximate various objectives such as the policy function, optimal Q-function, and even the reward function.

Unlike the aforementioned approaches, unsupervised learning is known to achieve significantly low training complexity compared to other types of learning algorithms. In other words, unsupervised learning is advantageous in time-varying and uncertain wireless systems, which may need various models to capture dynamically changing behaviors, based on the potential of the simple training algorithm. For this reason, unsupervised learning-based resource allocation schemes, which include transmit power allocation, channel allocation, and user selection, are proposed in divergent systems such as device-to-device networks [15], [16] or non-orthogonal transmissions [17]–[19].

III. Future Trends and Challenges

1) Limitations of Single Deep Learning Algorithms: The above-mentioned three types of deep learning-based algorithms are effective and widely used in many kinds of research, but they have some disadvantages due to their inherent training methods. The supervised learning methods generally suffer from the high complicated-labeled data generation issues, while the reinforcement learning methods are trained by trial-and-error-based training, which incurs huge overheads in the training. On the other hand, due to the uncomplicated training algorithm, the unsupervised learning methods may not achieve the desired performance. Therefore, in the future, it needs to integrate heterogeneous learning methods for utilizing their own advantages, as in [20], [21].

2) Practical Implementation: Since most deep neural networks consist of static structures, the deep learning methods are difficult to be compatible with instantaneously changing wireless systems. For this reason, in [6], the graph neural network-based resource allocation scheme is proposed to correspondingly tune with varying input and output sizes of neural network structure. It should be more beneficial in practical wireless systems with a large number of devices in uncertain deployment scenarios.

3) Using Imperfect Channel State Information: In wireless systems, it is challenging to guarantee the perfect channel state information (CSI) due to the estimation error. The recent studies in [15], [17] leverage the deep learning-based training algorithms to compensate for the performance degradation of inaccurate CSI. From the performance results, it is shown that deep learning methods have the potential to avoid channel estimation errors.

IV. Conclusion

In this paper, we have introduced deep learning-based resource allocation algorithms, which are mainly classified into three types. From the prior studies, it is shown that deep learning can improve resource allocation performance and achieve a low complexity than conventional iterative algorithms. In addition, discussions of limitations and practical issues are presented to provide insights into future research.

Acknowledgement

This work was supported by the Korea government (Ministry of Science and ICT) in part under the National Research Foundation of Korea (NRF) grants (NRF-2022R1A4A3033401, NRF-2022R1F1A1065367, NRF-2022R1A2C1003388) and in part under the ITRC support programs (IITP-2023-2021-0-02046) and in part under the Convergence security core talent training business support program (IITP-2023-RS-2023-00266615) supervised by the IITP.

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