Graph Neural Networks for Communication Networks: A Survey

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***Abstract*— Communication networks are an important infrastructure in contemporary society. In recent years, based on the advancement and application of machine learning and deep learning in communication networks, the most advanced deep learning method, Graph Neural Network (GNN), has been applied to understand multi-scale deep correlations, provide generalization ability, and improve the accuracy indicators of predictive modeling. In this survey, we reviewed various issues using different graph based deep learning models in different types of communication networks. Optimize control strategies, including offloading strategies, routing optimization, resource allocation, etc. Finally, we discussed potential research challenges and future directions.**

Keywords—deep learning, graph neural networks, reinforcement learning, network modeling, communication networks

I. Introduction

The growth of communication networks also brings new challenges. This not only includes traditional challenges such as routing and load balancing, power control, and resource allocation, but also emerging challenges such as virtual network embedding in SDN.

With the popularization of large-scale wireless communication solutions, such as large-scale multi-input multi-output (MIMO), corresponding mathematical models have become more complex, and related optimization algorithms have higher computational complexity. On the other hand, ML technology, especially deep learning (DL) technology, has strong representation capabilities and low inference complexity for various neural network models. Therefore, recent work has applied DL technology to wireless communication, such as resource allocation, physical layer design, and network modeling.However, in these studies, network topology has not been fully utilized, as most deep neural networks are designed for Euclidean structured data. In recent years, graph based deep learning represented by graph neural networks (GNN) has been proposed for non-Euclidean structured data[4]. In recent years, GNN has also been combined with deep reinforcement learning to make decisions in a series of problems.

As a special graphical data neural network model, Graph Neural Network (GNN) has achieved good performance in various graph related applications and has the potential to address the aforementioned challenges. GNN utilizes graph information, especially graph topology information, more effectively than other neural network models, which may reduce the number of required training samples. Secondly, GNN can handle input graphs of different sizes.

II. Advantages of Graph Neural Networks in Communication Networks

GNN is an efficient graph analysis tool. GNN can be naturally applied to wireless networks. More importantly, GNN has several special characteristics that are particularly suitable for the characteristics and requirements of wireless communication. They have great potential for overcoming the challenges of using ML in wireless communication mentioned above.

Firstly, GNN learns low dimensional vector representations by simultaneously extracting node/edge features and topology information. However, topological information is high-dimensional, making it difficult to fully utilize traditional mathematical techniques and other neural network models, such as CNN and Recurrent Neural Networks (RNNs). Therefore, for various tasks in wireless communication, using GNN may achieve better performance with fewer training samples.

Secondly, the parameters of each GNN layer are shared among all nodes in the graph. Therefore, GNN has good generalization ability for input size, which is particularly suitable for the dynamic characteristics of wireless communication.

Finally, GNN only updates the embedding vectors of nodes based on neighborhood information. As shown in 'Fig1', once the GNN model is trained and deployed, the inference phase can be implemented in a decentralized manner. More specifically, each node only needs to exchange information with its neighbors and can obtain its own prediction results locally. Most neural network models widely used in wireless communication, such as CNN and RNN, require central processing during the inference phase. Therefore, GNN can promote decentralized control and resource management, which is very attractive for large-scale wireless communication systems.

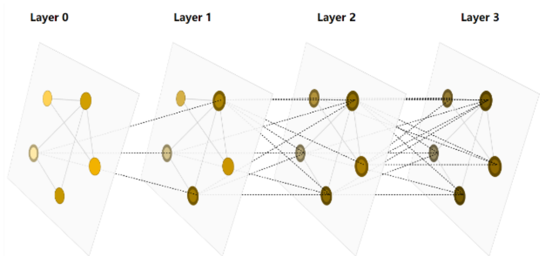

Fig. 1.

III. General Scenarios

In this section, we focus on relevant research in wireless network scenarios. In large-scale MIMO, accurately extracting spatial correlation can help neural networks track time-varying large-scale MIMO channels, thereby improving the quality of data transmission. A channel tracking method based on graph neural networks for large-scale MIMO networks was proposed in [6], targeting the channel tracking problem in high-speed mobile scenarios. This method first utilizes a small number of pilot signals for initial channel estimation, and then represents the obtained channel data in the form of a graph, and describes the spatial correlation of the channels through the weights on the edge of the graph. A channel tracking framework has been designed, which includes an encoder, core network, and decoder.

Effective channel allocation in high-density wireless local area networks can avoid competition between wireless access points, effectively control channels, and improve throughput.A channel allocation scheme [7] based on deep reinforcement learning and graph convolutional networks was proposed, which extracts the features of carrier perception relationships between APs through GCN and collects training data using SAP method to improve learning speed.

Power allocation in wireless networks optimizes network performance and resource utilization by adjusting signal strength and coverage. In the study of power allocation problems in wireless self-organizing networks [8], a hybrid method was proposed, which combines traditional model-based methods with data-driven methods to propose a neural network architecture called Unfolded WMMSE (UWMMSE). It parameterizes learnable weights through GNN and trains based on gradient descent methods for multiple power allocation problems.This architecture has permutation and other variability, which is conducive to promotion between different network topologies.

In heterogeneous networks, [10] mentioned learning power allocation strategies in multi region and multi user radio systems, which is a type of heterogeneous network. The literature proposes a heterogeneous graph neural network called PGNN, which learns power allocation strategies, and how to design parameter sharing schemes to meet the required permutation and other variable attributes.In traffic prediction,[11] introduces a network traffic prediction method based on deep graph sequence space-time modeling. This method combines technologies such as mobile virtual reality, artificial intelligence, and vehicle networking, aiming to achieve high throughput, low latency, and high reliability service guarantee. A Space Time Graph Convolutional Gated Recurrent Unit (GC-GRU) model is proposed.

Resource management in wireless networks is a key aspect to ensure efficient network operation and full resource utilization. In [11], a distributed resource allocation strategy learning method based on GNN was introduced, which can handle the decentralized optimal resource allocation problem in wireless networks with local information structures. The method utilizes Aggregation Graph Neural Networks (Agg GNNs) to process a series of delayed and possibly asynchronous graph aggregation state information locally obtained by each sender from multi hop neighbors. Utilizing model-free primal dual learning methods to optimize performance while meeting both latency and asynchrony in decentralized networks. The study also explored the permutation and other variability of the obtained resource allocation strategies, which can promote the transmission of dynamic network structures.

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III.B. Cellular Network

Cellular networks are a crucial communication technology, with research directions covering multiple key areas. There is also a discussion on channel estimation in cellular networks. This article [14]mainly introduces a channel estimation method for the full duplex reflective intelligent surface assisted high altitude platform station (HAPS) backhaul link based on graph attention networks (GAT). The literature first applied graph attention networks to channel estimation, improving performance and reducing computational complexity. A method for channel estimation in full duplex mode was proposed, which can simultaneously obtain two channel coefficients of reflective intelligent surfaces. More importantly, the provided method can be easily extended to multi user and MIMO RIS assisted wireless communication scenarios.

In addition, there are more detailed discussions on methods in network slicing, such as combining reinforcement learning methods, and the use of digital twin technology[16]. There are multiple important directions in cellular networks, such as power control. Research on how to achieve intelligent prediction and control of power allocation for mobile users through techniques such as graph reinforcement learning and graph neural networks, in order to optimize network performance. In [2], we explore a method based on deep graph reinforcement learning for intelligent traffic routing control, especially in software defined wireless sensor networks.

III.C. Other wireless scenarios

These cited studies focus on multiple key topics such as the Internet of Things, the Internet of Vehicles, and satellites, such as D2D communication, wireless link scheduling, Internet of Things networks, anomaly detection, intrusion detection, etc. The research adopts advanced technologies such as graph convolutional networks, deep reinforcement learning, beamforming, and graph neural networks to optimize resource allocation, improve performance, enhance security, and improve network management.

In the D2D wireless communication network architecture, terminal devices in the network (such as smartphones or IoT devices) can communicate directly without the need for traditional base stations or relay nodes. This direct communication between devices can be used in various application scenarios without relying on traditional network base stations. This article [18] proposes a fully decentralized multi-agent reinforcement learning algorithm, FDS-MARL, in a device to device communication (D2D) environment to address joint optimization of collaborative caching and retrieval, in order to minimize overall content acquisition latency. It adopts design components such as graph attention network self -attention coordination, consensus communication mechanism, and impact based transmission scheduling mechanism, which can significantly improve content caching and retrieval performance.

Security issues in the Internet of Things. In article [21], the proposed E-GraphSAGE can capture edge features of graphs and topology information in network intrusion detection. This indicates the potential of GNN in the field of network intrusion detection. This is a GNN based Network Intrusion Detection System (NIDS), which is more suitable for processing stream data and can better solve the problem of network intrusion detection. There are also [19] improved E-miniGraphSAGE and E-ResGAT algorithms that utilize residual networks and graph attention networks to handle intrusion detection problems. Both algorithms use residual learning and address the issue of category imbalance in the dataset by adding residual connections.

Resource allocation in cellular networks [10] This literature proposes a supervised framework to address the complexity of D2D resource allocation in the Internet of Things. This framework models wireless networks as directed graphs, communication links as nodes, and interference links as edges, effectively optimizing link scheduling and channel power allocation. The application of blockchain technology to the Internet of Things has become a trend, aiming to provide high-quality services while minimizing energy consumption. In order to effectively reduce network energy consumption, a method called Request GCN-LSTM is proposed to capture spatiotemporal request patterns and predict data requirements in blockchain based IoT networks. The predictive based heuristic algorithm introduced is used to optimize the pre caching strategy, ensuring that the average data retrieval delay is minimized while considering the constraints of physical caching and data freshness in IoT networks.

A traffic prediction model based on the spatiotemporal dependence of satellite network traffic was introduced in satellite networks [4]. The topology of the satellite network was learned through GCN and the spatial features of traffic data were extracted. Then it is transmitted to GRU to capture the temporal changes in satellite node attributes, extract the temporal characteristics of traffic data, and finally perform traffic prediction. The use of GNN for communication delay modeling[13], load prediction, and resource allocation in the Internet of Vehicles [12] mainly studies the spectrum allocation problem in the Internet of Vehicles. By representing the communication network between vehicles as a graph, a graph neural network (GNN) is used to learn the low-dimensional features of each node, and then multi-agent reinforcement learning (RL) is used for spectrum allocation. Finally, a deep Q network is used to learn and optimize the total capacity of the V2X network.

IV. Wired network scenarios

Wired networks rely on physical wired connections, such as Ethernet, fiber optic, and other transmission media, to achieve high-speed and reliable data transmission and communication requirements. In this section, we first discuss graph based research in wired network scenarios from five aspects: network modeling, network configuration, network prediction, network management, and network security. Then we further discussed the applications in blockchain platforms, data center networks, and optical networks.

IV.A. General network

GNN can also play a significant role in intrusion detection in wired networks, such as BGP anomaly detection [17].This article mainly introduces a BGP anomaly detection framework based on a multi view model. The framework uses STL method to denoise raw time series data, and uses Graph Attention Networks (GAT) to discover the relationships between features and their temporal correlations, respectively, to capture abnormal behavior in BGP update traffic. The author validated the effectiveness of this model through extensive experiments and extended it to classify multiple anomalies and detect unknown events. There are also relevant models in botnet detection, such as the botnet detection model using GAT [9], and automatic detection botnet technology[22].

The application of GNN in encrypted traffic classification in wired networks has potential importance. The increase in encrypted traffic poses a challenge to traditional traffic classification methods. To address this issue, a new network traffic classification method has emerged\cite{b23}, taking into account the original bytes, metadata, and relationships between data packets. The use of GNN models to improve the performance and accuracy of encrypted network traffic classification has brought new possibilities to the field of network traffic recognition. A novel encrypted traffic classification method was proposed in \cite{b20}, utilizing a graph convolutional network and autoencoder based encrypted traffic classification method. This method utilizes traffic structure and traffic data to learn feature representation, and constructs a KNN traffic graph to express the structure of traffic, which can achieve higher classification accuracy with very little labeled data.

In conventional wired networks, graph neural networks (GNN) have a wide range of applications, including performance prediction, routing optimization, and traffic prediction [17]. In terms of network topology modeling, a graph neural network model called RouteNet [6] can accurately predict end-to-end key performance indicators (such as latency or jitter) in the network. RouteNet utilizes the structure of graph neural networks to model the complex relationships between network topology, routing, and input traffic, thereby achieving the ability to predict performance in network scenarios not seen during training. The article challenges RouteNet's generalization ability by showcasing its generalization ability in more complex scenarios, including larger topological structures.

IV.B. Optical Network

Optical networks, also known as optical communication networks, use optical fibers as transmission media to convert data into optical signals and transmit them in the form of light. The application discussed in this article in optical networks focuses on traffic prediction [1], resource allocation, and routing optimization techniques combined with reinforcement learning. [2] explores how to combine graph neural networks (GNN) with deep reinforcement learning (DRL) to solve network optimization problems, especially routing optimization problems. The literature proposes to apply GNN to DRL proxy to achieve generalization ability for any network topology, thus enabling DRL technology to be applied in production networks.

IV.C. Data Center Network

Data center network is a computer network designed specifically for data center environments, aimed at supporting high-performance, high availability, low latency, and efficient data communication within the data center. For the modeling of data center networks, [24] proposed a GNN model for flow completion time (FCT) inference, which can accurately estimate unseen network states. And designed a GNN based TO optimizer for flow routing, scheduling, and topology management. Resource allocation can also be utilized in data center networks, and the resource allocation problem in resource dispersed data center systems (RDDCs) was studied in [25]. The RDDC system has higher requirements for the network, requires more infrastructure, and has higher costs and power consumption issues. This paper introduces a resource allocation method based on reinforcement learning, which is used to manage server and network resources in resource dispersed data centers and can maintain performance when expanding to RDDC topology with more nodes than during training.

V. Conclusion

Graph neural networks have broad future potential in the field of network communication. It is widely used in resource allocation, channel estimation, and network optimization problems. His main advantage lies in its ability to extract features from the topology of nodes and edges, thereby better capturing network dependencies, which is very useful for modeling and optimizing communication networks. In terms of resource allocation, GNN has been used to solve radio spectrum allocation, improve multi user and multi task performance, and improve the accuracy and efficiency of channel estimation. In terms of network optimization, it can be used to solve problems such as network topology design and link prediction. Overall, GNN has broad application prospects and research value in the field of communication.

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