Applications and Perspectives of Graph Neural Networks in Power System

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Abstract: Graph Neural Networks is the evolution of a traditional neural network, which is a new technology to analyze graph data and makes up for the deficiency of traditional neural network that is difficult to process graph data. This paper introduces the concepts of Graph Neural Networks, compares and contrasts the differences between Graph Neural Networks and traditional neural networks, summarizes the application status of graph neural networks at home and abroad, and gives the direction of the application of graph neural networks in power systems.

Keywords: Graph Neural Networks; power systems; models; application scenarios; perspectives

1. Introduction

In recent years, research has been driven by semi-supervised or unsupervised approaches in pattern extraction and data analysis. Deep learning is even more centralized and has made significant contributions in areas such as machine translation and speech recognition that rely on extracting information features. Nonetheless, the above methods are only applicable to grid data and are difficult to harness non-Euclidean data such as graph data.

The rapid growth of the Internet of Things (IoT) has profoundly impacted several interconnected systems such as smart manufacturing, food supply chains, intelligent transportation systems, and healthcare infrastructure. The number of measurement recording devices in these interconnected systems has proliferated, generating a large amount of corresponding system data that reflect the relationships between physically interconnected systems, which, unlike grid data, do not have a fixed connection pattern and cannot be directly processed by traditional convolutional neural networks. Scholars at home and abroad are beginning to consider upgrading and optimizing deep learning methods, which are applied to the analysis and mining of graph data. Thus, after synthesizing the internal core concepts of Convolutional networks, Cyclic networks, and Deep self-encoders, the related personnel gave birth to Graph Neural Networks.

In this paper, we first introduce the relevant models and concepts of Graph Neural Networks. Then we give the application prospects of Graph Neural Networks in power systems in light of the extracted characteristics and the current status of power systems. Finally, we summarize some shortcomings and problems to be solved in Graph Neural Networks to provide directions and ideas for subsequent research.

2. Models of Graph Neural Networks

A graph is composed of vertices and edges [1]. In graph data, the vertices represent the entities mapped by the data, while the edges represent the relationships between entities [2]. Thus, graph data is a kind of structured data that describes the properties of entities and the relationships between entities, graph data generally has no uniform format and rules, and its complexity and orderliness are difficult to standardize. These properties add obstacles to the application of traditional neural networks [3].

However, Graph Neural Networks do not require data meshing, and only need to acquire interrelationships between nodes to perform calculations, and this algorithmic feature applicable to graph data solves the above problems. The kernel of a graph neural network is similar to that of a traditional neural network. It maps high-dimensional information into low-dimensional vectors and preserves as much of the original information as possible [4]. Diagram of Graph Neural Networks training structure is shown in Figure 1.

To date, the following approaches have been derived from the idea of Graph Neural Networks: Graph Convolutional Neural Network s (GCNs), Graph Attention Networks (GATs), Graph generation adversarial networks (GraphGANs), and Graph self encoders (GAEs).

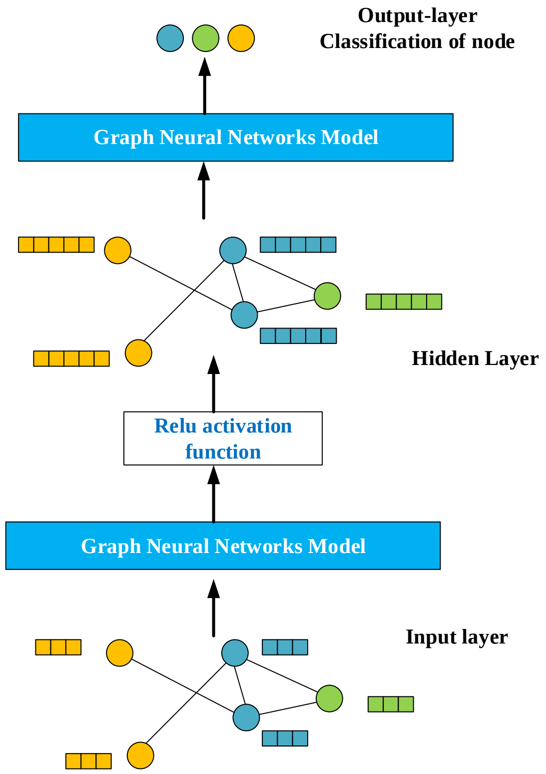

Figure 1. Diagram of Graph Neural Networks training structure

Graph Convolutional Neural Network (GCN): for the graph data in the input layer, by collating and fusing the features with the vertices around the vertices, all the aggregated feature information in the graph data is compressed to each vertex in the hidden layer, thus realizing the compression of the graph data from high dimension to low dimension, and finally, the aggregated feature information is mapped to the output layer through the activation function to complete the low dimensional expression of the data. Reference [5] applies graph convolutional neural networks to solve the link importance problem. Reference [6] applies a graph convolutional neural network to achieve a hidden layer representation of local graph structure and node features for encoding. Reference [7] invoked a graph convolutional neural network to classify and identify the data and showed that the GCN algorithm has higher recognition accuracy than the CNN and K-nearest neighbor (KNN) algorithms, especially in the case of the low signal-to-noise ratio. Reference [8] applied graph convolutional neural networks to classify and categorize Alzheimer's disease, and the method has been experimentally demonstrated to have high accuracy.

Graph Attention Network (GAT): can be seen as a technical upgrade to GCN, a network structure that combines graph convolution and attention mechanisms. Based on the GCN processing graph, the idea of attention is introduced to calculate the importance of each neighboring node to it, and then to obtain the overall information of the whole network from the local information, while stacking these hidden from attention layers to obtain the characteristics of neighboring points, avoiding a large number of matrix operations and computationally efficient. Reference [9-11] applies graph attention networks in traffic prediction to achieve coordinated and controllable real-time traffic. Reference [12] applies a graph attention network in recommendation problem to automate medical diagnosis. Reference [13,14] applies a graph attention network in multi-channel pattern recognition with high accuracy.

Graph generation adversarial network (GraphGAN): integrated generative network model and discriminative network model in one, calculate the probability of association between vertices, and then through the two models of self-game, confidence in the relationship with a higher probability of association, thus completing the analysis and prediction of graph data. Reference [15] demonstrates, through extensive experiments on real-world datasets, that GraphGAN is capable of performing tasks including graph reconstruction, link prediction, node classification, recommendation, and visualization. Reference [16] applied graph generation adversarial networks in both node classification and link prediction tasks and experimentally demonstrated that the accuracy of the method exceeded that of traditional approaches.

Graph self encoder (GAE): different from the above semi-supervised learning mode, the graph self encoder is an unsupervised learning method. The method is composed of encoder and decoder, which first learns the distribution patterns and features of graph data through some variables, acquires potential representations, completes the encoding function, and then reconstructs the original graph through an individual decoding first segment through the learned potential representations to complete the internal analysis and mining of the graph data. Reference [17] applies graph self-coding for denoising graph signals and experimentally demonstrates better performance than existing methods in experiments involving real traffic signals. Reference [18] proposes a graph regularized stacked denoising autoencoder (G-SDAE) network, which has been experimentally demonstrated to have high detection accuracy and reliability. Reference [19] proposed a local feature hash model with graph-regularized binary autoencoders to learn feature representations for facial recognition, and experimental results show that the model outperforms most face representation methods.

In summary, the core idea of these methods is to map the number of vertex features in the graph data to low-dimensional vectors, which helps to extract features from the graph data more efficiently and use them for analysis and prediction. The difference lies in the technical route, computational performance, and application scenarios.

3. Applications and Perspectives of Graph Neural Networks

Today's graph neural network research involves many directions, covering many areas of socio-economic development. In the following paper, the application of the graph neural network method is described in several directions for the task scenarios and characteristics of the power system.

3.1. Intelligent Dispatching

In the intelligent dispatching operation of power systems, it is crucial to accurately predict the massive load nodes and lines in the power network and to detect the weak links in the system operation for the safe operation of the power system. The power network visualizes as a Spatio-temporal graph, where nodes are sensors that sense the state of this Spatio-temporal graph. As a typical graph data, the graph neural network can mine the data to obtain the "vertex" and "edge", node and line operation state, and solve the prediction problem of line energy flow (power size).

3.2. Automatic Substation Inspection

Graph neural networks can also be applied in computer vision. We use visual reasoning to treat the collected visual graph of the device operating state as a kind of graph data. We can then analyze and predict this graph data through graph neural networks to estimate the device operating state. Finally, combined with the historical data, we explore the primary state of the equipment operation, thus further exploring its operational boundaries as an information retrieval repository for the prevention of failures.

3.3. Planning of Charging Stations

Based on the demand for new energy vehicles, location information, weather data, and event characteristics, the network embeddings trained by combining the above features are combined to form a multi-source information integrated graph data. Through the joint representation of each location, the map data is processed to predict the number of charging stations in a particular location at a particular time, and the planning scheme that can meet the demand to the maximum extent possible is obtained through comprehensive cost consideration.

3.4. Recommendation System

By taking advantage of the relationship between users and electricity consumption information, we transform the recommendation system-related problem into a link prediction problem. It allows us to analyze the customer's electricity consumption behavior. By rating and classifying users, we can recommend electricity packages that fit their behavior.

3.5. Problems Related to the Knowledge Graph

Since the knowledge graph is a kind of graph data, the combination of graph neural network and knowledge graph becomes a new means to solve all kinds of knowledge graph problems. Some results have been reflected in practical applications. The literature [20] chooses to model the knowledge graph with graph neural network, and the GNN-based approach can better capture the ternary group compared to the previous reasoning based on individual ternary group relations. The complex and hidden pattern information of neighboring domains enables the relational complementation of knowledge graphs. The literature [21] proposes a GNN-based entity alignment scheme, which has been shown experimentally to have the highest data consistency and improve the quality of the knowledge graph on multiple datasets.

4. Some Pressing Issues for Graph Neural Networks

Although many research results have proved the capability of GNN in mining graph data, the complexity of application objects still poses a challenge to GNN, and there are still some problems with the algorithm itself, which need to be overcome and optimized step by step by researchers and scholars. The specific optimization directions are organized as follows.

- The problem of the computational efficiency of Graph Neural Networks, the learning effect of the neural network is directly related to the number of convolutional layers. For GCN, increasing the number of convolutional layers means an exponential decrease in computational efficiency. How to optimize the algorithm so that it can have good scalability is a problem that needs to be solved in the future.
- How to select an optimization algorithm and optimization aggregation function in aggregated neighborhood feature measures. Up to now, the aggregation function is mostly used as a direct method to extract the aggregated features by directly adding or de-averaging them. However, this method of compressing the information from high dimension to low dimension is at the cost of losing most of the information, so how to construct an aggregation function that can preserve the original information as much as possible and run the computation efficiently is a problem worth solving.
- The scalability of the algorithm, in general, when the missing part of the graph data leads to the lack of information between nodes, the laws and features learned are not enough to support the algorithm's mastery of the unknown nodes, which directly affects the analysis and mining results. How to construct a graph neural network optimization algorithm that can satisfy the real mining of unknown feature quantities is a pressing problem.
- For static graphs, graph neural network analysis is better. However, for dynamic graphs, the acquired knowledge cannot fully control the dynamic graph, and the acquired knowledge is not sufficient to support the determination of the unknown entity-relationship when the relationship (topology) between some of the methods is changed. How to optimize the algorithm so that the graph neural network can adapt to the variable structure of the graph data is also a pressing issue.
- Graph neural networks are similar to neural networks. They have the same problem: the black box problem. Although after an iterative training process, we can analyze the relevant data and obtain credible classification results. However, the weight matrix trained is challenging to portray and describe with accurate information. Therefore, the

interpretability of graph neural networks is also a matter of concern.

5. Summary

Based on the review of graph neural network models and kernels, this paper gives some application scenarios of Graph Neural Networks in power systems and lists some shortcomings and problems to be solved in the future. It provides some ideas and directions for further research.

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