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Graph Neural Network Model and Application

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Abstract—In recent years, graph neural network (GNN) has become a research hotspot in various fields, and the application of GNN is explored in various fields, such as natural language processing, computer vision and industrial recommendation applications. GNN is good at processing unstructured data, which enables data to be represented and learned through graphs, strengthens the connection between graphs, and makes new progress in network data analysis, recommendation system, natural language processing and other aspects. This paper mainly analyzes the different graph neural network technology and the different applications of graph neural network, and looks forward to the future development and research direction of graph neural network.

Keywords—*Graph Neural Network; Model; Application; Development*

I. INTRODUCTION

In recent years, with the rapid development of the computer industry and the exponential growth of the amount of data, deep learning has been proposed and widely applied. Deep learning has achieved great success in image processing, speech recognition, semantic understanding and other fields through the end-to-end solution of neural networks. Applications of deep learning are usually Euclidean data with regular feature distribution in high-dimensional feature space.

With the emergence of computer and the arrival and development of machine computing era, graph, as an important data structure that can effectively and abstractly express the entity in information and data and the relationship between entities, has been widely used. Graph database effectively solves the problems such as many modeling defects and slow computing speed exposed by the traditional relational data structure in the face of a large number of complex data. Graph database has also become a very hot research field. Graph structure can connect data nodes of different types and structures according to the relationship between data through the form of structured data points, so it is widely used in data storage, retrieval and calculation applications. Based on the graph structure data, knowledge graph can accurately describe the relationship between entities in the real world through the semantic relationship between points and edges. As a very important research field of artificial intelligence, the research directions of knowledge graph include knowledge extraction, knowledge reasoning, knowledge graph visualization, etc.

II. GRAPH STRUCTURE DEFINITION

To solve the representation problem of non- Euclidean structured data, researchers introduced the abstract Graph in graph theory to represent non-Euclidean structured data. The graph is defined as $G = (V, E)$, and its structure is shown in Figure 1 below.

As shown in the figure, we can get a set of points and a set of edges. $V = \{1,2,3,4,5,6\}$, $E = \{E1,E2,E3,E4,E5\}$. The input to GNN is a graph, the output is a graph, and it transforms the properties of your graph (points, edges, global information), but it doesn't change the graph's connectivity, which edges connect which vertices, this information doesn't change.

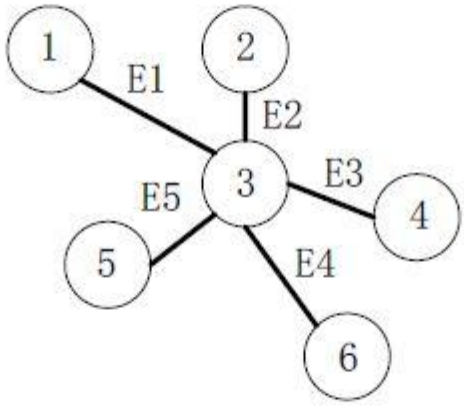

Figure 1: Graph Structure

III. FIGURE NEURAL NETWORK MODEL

There are many variant models of graph network. This paper mainly discusses graph convolutional neural network and graph attention neural network.

A. Graph convolutional neural network

Graph convolutional neural network(GCN), It is a method that can carry out deep learning of graph data. It utilizes the continuous aggregation of information of nodes and their neighbors to learn the high-level representation of nodes. As shown in equation (1).

$$hil+1=\sigma(\Sigma j\in Ni1cijhjlwRjl) \quad (1)$$

Where hjl is the characteristic expression of i in the l layer. cij is a normalization factor, like taking the reciprocal of node degrees. Ni is the neighbor of node i and contains itself. Ri is the type of node i . $wRjl$ represents the transformation weight parameter of the type node.

Process of graph convolution: Step 1: send each node sends its own feature information to its neighbor node after transformation. This step is to extract and transform the characteristic information of the node. Step 2: receive Each node collects the characteristics of its neighbors. In this step, the local structure information of the node is fused. Step 3: transform Aggregate the previous information and perform nonlinear transformation to increase the expression ability of the model.

Four features of GCN: (1) GCN is a natural extension of convolutional neural network on graph domain. (2) It can simultaneously learn node feature information and structure information end-to-end, which is the best choice for graph data learning task at present. (3) The applicability of graph convolution is extremely wide, which is applicable to nodes and graphs of any topology structure. (4) In the tasks of node classification and edge prediction, the effect of open data set is much better than other methods.

B. Graph attention network

Graph attention network(GAT), It uses the attention between nodes to calculate the attention coefficient between nodes and neighboring nodes, and then obtains the feature representation of the next layer by aggregating the neighboring nodes. Layer input: $h=\{\vec{h}_1,\vec{h}_2,\ldots,\vec{h}_N\}, \vec{h}_i\in\mathbb{R}^F$, Layer output: $h'=\{\vec{h}'_1,\vec{h}'_2,\ldots,\vec{h}'_N\}, \vec{h}'_i\in\mathbb{R}^{F'}$. At least one learnable linear transformation is required in order to obtain sufficient expressiveness to transform input features into higher-level features. Thus, as a first step, a shared linear transform $W\in\mathbb{R}^{F'\times F}$, parameterized by a weight matrix is applied to each node. Then, the attention mechanism of self-attention sharing is implemented on the node, and the attention coefficient is calculated. As shown in equation (2).

$$e_{ij}=a(W\vec{h}_i,W\vec{h}_j) \quad (2)$$

For the attention mechanism in graph neural networks, it can be simply understood that the convolutional activator in general graph convolutional neural networks is replaced by the attention module. In different methods, the weight parameters of the perceptive domain of the attention mechanism can be improved by combining gating information to achieve better reasoning and application performance. Graph convolutional neural network realizes node classification of graph structured data, and attention mechanism has a very good effect and performance in the field of natural language processing. For the Graph Attention Network, the process of summing features of neighbor nodes is completely different from that of the graph convolutional neural network. The global attention mechanism replaces the solidification operation of convolutional hierarchical transmission. Nodes or subgraphs, models, and paths that are more important in the graph structure can be efficiently selected to assign greater attention weight.

IV. GRAPH NEURAL NETWORK APPLICATION

A. Natural language processing

GNNs has many applications in natural language processing, including multi-hop reading, entity recognition, relation extraction and text classification. Multi-jump reading refers to the open-ended reading comprehension that gives the machine a lot of corpus, allows the machine to conduct multi-chain reasoning, and then answers a complicated question. In 2019, the top paper on natural language processing showed the scope of applications in natural language processing.

B. Computer vision

Applications in computer vision have images generated according to the semantics provided. Talking about visual reasoning, human processing visual information is often mixed with reasoning. Human beings can reason from spatial or semantic dimensions, and graphs can depict spatial and semantic information well, so that computers can learn to use such information to reason like human beings. Of course, there are motion recognition, visual questions and other applications, we won't list them here.

One of the biggest applications of graphic neural networks is computer vision. Researchers have explored the use of graph structure in many aspects such as scene graph generation, point cloud classification and segmentation, and action recognition.

In scene graph generation, semantic relationships between objects help to understand the semantic meaning behind visual scenes. Given an image, the scene graph generates models that detect and recognize objects and predict semantic relationships between pairs of objects. Another application reverses this process by generating an actual image of a given scene diagram. Natural language can be parsed into semantic graphs, where each word represents an object, which is a promising solution for synthesizing a given text description image.

In point cloud classification and segmentation, point cloud is a group of three-dimensional points recorded by lidar scanning. The solution for this task enables lidar devices to see their surroundings, which would normally benefit driverless vehicles. In order to identify the objects depicted by the point cloud, the point cloud is transformed into K-nearest neighbor graph or superposition graph, and the graph theory evolutionary network is used to explore the topology.

In motion recognition, recognizing the human actions contained in a video helps to better understand the content of the video from the machine side. One set of solutions detects the position of human joints in video clips. The body's joints, which are connected by bone, naturally form diagrams. Given the time series of human joint position, space-time neural network is applied to learn human behavior patterns.

In addition, the possible directions of application of graphic neural networks in computer vision are also increasing. These include human-object interaction, classification of images with fewer shots, semantic segmentation, visual reasoning, and question and answer.

C. Recommendation system

Recommendation is an important application of machine learning in the Internet. In the Internet business, the recommendation scenario is especially said, such as content recommendation, e-commerce recommendation, advertising recommendation and so on. Here, we introduce three recommended methods of graph neural network empowerment. The graph-based recommendation system takes items and users as nodes. By using the relationship between item and item, user to user, user to project and content information, the graph-based recommendation system can generate high-quality recommendations. The key of the recommendation system is to evaluate the importance of an item to the user.

CONCLUSION

In recent years, graph neural network has been developed rapidly in many fields. The rich application value of graph data encourages more researchers to join in the study of graph data. However, when analyzing graph data, we need to consider the characteristic information and structural information of nodes at the same time. For the GNN model, we introduce variations based on the compute module, graph type, and training type. In terms of application classification, there are various application scenarios of GNN, and the main challenges and future research directions of neural networks are illustrated. We believe that the application of GNN will cover all aspects of our life in the future, and there will be better innovation in the future.

References

[1] Zhou J, Cui G, Hu S, et al. Graph neural networks: A review of methods and applications[J]. AI Open, 2020, 1:57-81.

[2] Wu Z, Pan S, Chen F , et al. A Comprehensive Survey on Graph Neural Networks[J]. IEEE transactions on neural networks and learning systems, 2021(1):32.

[3] Zhang J . Graph Neural Networks for Small Graph and Giant Network Representation Learning: An Overview[J]. 2019.

[4] Liu Y , Pan S , Jin M , et al. Graph Self-Supervised Learning: A Survey[J].2021.

[5] Zhang Z , Cui P , Zhu W . Deep Learning on Graphs: A Survey[J]. IEEE Transactions on Knowledge and Data Engineering, 2020, PP(99):1-1.