Chapter 6
Fundamental Concepts in Graph Attention Networks

R. Soujanya
Gokaraju Rangaraju Institute of Engineering and Technology, Hyderabad, India

Ravi Mohan Sharma
https://orcid.org/0000-0001-5750-0450
Makhanlal Chaturvedi National University of Journalism and Communication, Bhopal, India

Manish Manish Maheshwari
Makhanlal Chaturvedi National University of Journalism and Communication, Bhopal, India

Divya Prakash Shrivastava
Higher Colleges of Technology, Dubai, UAE

ABSTRACT

Graph attention networks, also known as GATs, are a specific kind of neural network design that can function on input that is arranged as a graph. These networks make use of masked self-attentional layers in order to compensate for the shortcomings that were present in prior approaches that were based on graph convolutions. The main advantage of GAT is its ability to model the dependencies between nodes in a graph, while also allowing for different weights to be assigned to different edges in the graph. GAT is able to capture both local and global information in a graph. Local information refers to the information surrounding each node, while global information refers to the information about the entire graph. This is achieved through the use of attention mechanisms, which allow the network to selectively focus on certain nodes and edges while ignoring others. It also has scalability, interpretability, flexibility characteristics. This chapter discusses the fundamental concepts in graph attention networks.

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INTRODUCTION

Graph Attention Networks, also known as GATs, focus on graph data in their analysis. The GAT is constructed using graphs of increasing attention levels that are stacked one over the other. The input for each graph attention layer is the node embeddings, while the layer's output is an updated version of the original node embeddings. While determining how the node should be embedded, the embeddings of the other nodes to which it is linked are considered (Velickovic et al., 2018).

It is possible to explain what a graph attention network is by saying that it makes use of the attention mechanism that is present in graph neural networks in order to address some of the flaws that are present in graph neural networks. Because of their skills of learning via graph data and producing more accurate results, graph neural processing is now one of the most popular study areas in the fields of data science and machine learning. A graph neural network and an attention layer have been combined to create what is known as a graph attention network.

The graph neural networks do quite well when it comes to categorising nodes based on the graph-structured data. Because of the way that graph structure aggregates information, graph convolutional networks may be reducing the generalizability of data that is arranged in a graph, which is one of the numerous shortcomings that we may uncover while investigating many of the difficulties. The use of a graph attention network to such issues can modify the way information is aggregated, which is one of the benefits of doing so.

The Graph Attention Network, also known as GAT (Velickovic et al., 2018), is a design for graph neural networks that makes use of the attention mechanism to learn the weights that are associated with linked nodes. In contrast to GCN, which employs weights that have already been calculated for the neighbours of a node that correspond to the normalisation coefficients, BCN uses weights that are randomly generated. The aggregation process of GCN (Zhou et al., 2020) is altered as a result of GAT's ability to understand, via the attention mechanism, the strength of the link that exists between surrounding nodes.

Instead of computing that coefficient directly, as GCNs do, the key concept behind GAT is that it should be done implicitly instead.

An operation that is statically normalised and convolutional can be provided by the attention, just as it is in GCN. As consideration is given to the network, the weights assigned to the more significant nodes during the neighbourhood aggregation process are increased.

Graph Attention Networks (GATs) have shown great promise in the field of graph representation learning, and there are several potential research directions that could further advance the state of the art (Verma, 2021):

1. **Incorporating Heterogeneous Graph Structures:** Most existing GAT models assume homogeneous graphs, where all nodes and edges have the same type. However, many real-world graphs are heterogeneous, with nodes and edges of different types. Future research could explore ways to extend GATs to heterogeneous graphs, allowing them to model more complex relationships between nodes.
2. **Handling Dynamic Graphs:** Many real-world graphs are dynamic, where nodes and edges are added or removed over time. Current GAT models are designed to work with static graphs, and it remains an open research question how to effectively model dynamic graphs.

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