GT Paper Review

Group Details:

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Title Of the Paper:

An End-to-End Multiplex Graph Neural Network for Graph Representation Learning

(Published by - IEEE)(Published on - 28/03/2021)

Introduction:

Graphs are known to have complicated structures and have a myriad of real-world applications. Recently, significant efforts have been put into utilizing deep learning methods for graph data analysis. Convolutional Neural Networks inspired many models which we have today for the purpose of neural network analysis.But such networks fail to keep up with the wide variety and ranges of graphs. Using a unified model can bring about trouble in the form of underfitting. In this paper, the writers have explored multiple ways to overcome this issue.

Literature Review:

The paper approaches Graph Neural Networks in a new way. The writers try out different approaches towards graph classification and end up with designing an MxGNN(Multiple Graph Neural Networks) to learn graph representations for graph level classification tasks.They have used four

datasets of protein from the bioinformatics domain and two social network datasets.All comparisons are made from a common baseline which is the GraphSAGE.GraphSAGE is a graph convolution framework proposed for semi supervised node classification.Out of all the dataset which was tested against the MxGNN, the baselines GIN(Graph Isomorphism Network) and SAGPool(Self Attention Graph Pooling) were seen to be better than MxGNN when it comes to the COLLAB dataset. But the MxGNN showed the highest accuracy in the rest of the considered datasets.
This shows a significant improvement over the current state of the art models utilizing graphs for graph representational learning.

Proposed Methodology:

The proposed methodology is graph representational learning with the help of MxGNN(Multiple Graph Neural Networks). MxGNN can be simply put to be a multi-layer hierarchical GNN model.The aim is to learn node-level representations while the pooling algorithm aims to learn a coarsened graph.The new coarsened graph is used as input to the next layer.This process continues repeating several times, generating a multi-layer GNN model.The pooling layer is DiffPool[6].MxGNN launches multiple GCN's(Graph Convolutional Network). These are then combined using graph's a priori properties.We also use Differential Pooling for vertically aggregating and summarizing the data.The same result is achieved horizontally with the help of GCN. The Coarsened Graph which we get at the end of these procedures is used as an input to the next iteration thus generating a MxGNN.

Results:

To compare the accuracy of the new proposed model to the existing baselines, there are 6 datasets considered in this paper for further analysis. Four protein datasets from the bioinformatics domain and the other two from the social network domain consisting of thousands of graphs.The baselines used are GraphSAGE,SortPool,GPool,SAGPool(Self Attention Graph Pooling) and GIN(Graph Isomorphism Network).It was shown that MxGNN performed better than all the baselines in 5 out of 6 of the

datasets. In the COLLAB dataset of the social network domain, the models GIN and SAGPool performed better than the MxGNN in terms of accuracy. The direct comparison to MxGNN is the DiffPool model since it is the most similar. The MxGNN model outperforms the Diff Pool model by an average of 1.79%.When it comes to convergence, on the ENZYME dataset, MxGNN converges at 280 seconds whereas DiffPool converges in at 600 seconds.Other models do not converge at 600 seconds. MxGNN is two times faster than DiffPool when it comes to time to Convergence.

Conclusion:

The paper proposed a simple but effective multiplex GNN architecture for graph representational learning (Hierarchical).The MxGNN is made up of multiple graph convolutional networks to learn node-level representations and use graph-pooling networks to coarsen the graph.To address the diversity challenge of graph representation learning, A priori graph properties are used to assign attention weights to the Convolutional network.The MxGNN seems to be leading the way in graph representational learning, but beating out its current competing methods in terms of accuracy. In the future, they expect this performance to improve by adding a multiplex pooling layer and unpooling layers based on encoder-decoder learning structure.