Fine Tuning a Role Discovery Network Based on Low-Rank Adaptation Principles

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1 Introduction

Role discovery is essential for uncovering hidden structural patterns and functions of nodes in complex networks. Analyzing node roles helps optimize strategies for advertising. In online social networks, users identified as "star-centers" are often seen as influencers and are highly effective in promoting advertisements. [1][2]. Nevertheless, traditional graph-based methods for role discovery may have some obstacles to capture complex roles in large networks. A feature-based role framework was proposed to address these issues, transforming graph data into features and assigns nodes with similar features to the same roles.[3][4].

Struc2vec specializes in capturing the structural identity of networks which is suitable for node representation learning.[5]. Kikuta et al. proposed a general framework that integrates network representation learning(using struc2vec), domain adversarial learning, and model selection method.[6]. Traditionally, unsupervised learning may face challenges in result validation. They introduced a validation network that simplifies model selection without relying on labels in a target network, using only few labeled network for validation [1]. Although the model demonstrated its superiority on multiple datasets, there are some shortcomings as well. In experiments with air traffic networks, the performance of model selection was close to, and in some cases slightly lower than struc2vec (Target tuned). Moreover, compared to the theoretically optimal performance, the proposed method still showed a performance gap. These findings indicate that there is still room for improvement in achieving higher accuracy and robustness in role discovery.

In recent years in the field of large language models(LLMs), as model sizes continue to increase, the traditional fine-tuning approach which requires to update all parameters of a pre-trained model has become increasingly impractical. For LLMs such as GPT-3, full fine-tuning is not only computationally expensive but also incurs significant storage costs[7]. LoRA (Low-Rank Adaptation) can significantly reduce trainable parameters for downstream tasks by freezing the weights of the pre-trained model and injecting trainable rank-decomposition matrices into each layer of the Transformer. LoRA presents several key advantages: it facilitates efficient task-switching through shared pre-trained models, enhances training efficiency by reducing hardware requirements, simplifies deployment with its linear design, and offers compatibility with various prior methods[8]. In a study on the spread of misinformation about Ivermectin as a treatment for Covid-19, researchers manually labeled influential users, and classify the pro-use users and anti-use users based on the frequency of their retweets of influencers who advocate for or against the use of Ivermectin[9]. There is still space for improvement, such as analyze content of the tweets of retweeters although extracting and analyzing the content from a massive volume of retweeted tweets can be challenging. Given LoRA's optimization for LLMs, we consider that LoRA can be further extended to research involving role discovery for processing information in text data, improving the accuracy of role discovery in social networks.

We proposed an idea that based on pre-trained struc2vec model, incorporating a new network in a bypass similar to the LoRA method to enhance overall performance.

2 Methodologies

2.1 Build Neural Network

Pretrained node representations: We use struc2vec for node representation learning which initialize the source and target domains and ensures nodes with similar structures have similar representations in each domain. Additionally, it ensures that structurally similar nodes have representations that are as close as possible in the other domain. This part is pre-trained and remains static without further updates or training.

Bypass network: Unlike other sequential adapter algorithms, LoRA incorporates a parallel matrix alongside the pre-trained LLM matrix, comprising matrix A and matrix B. Matrix A acts as a dimensionality reduction matrix, decreasing the rank of the original matrix from d to r, where $l \ll d$; whereas matrix B functions as a dimensionality expansion matrix, elevating the rank from r to d.[8]. This approach is more like adding a modified neural network on the side of the original neural network. Not only can this method be applied to transformer-based large models, but we also believe it can be extended to other types of neural networks. Alternative approaches, such as integrating MLP or CNN, are under consideration. In essence, we aim to investigate diverse network architectures within this context. Our future work involves designing bypass networks for this part and train the network like the process of LoRA. The network we have designed, as illustrated in Fig.1, where x represents the input data and h denotes the output results, utilizes LoRA. In our approach, the pre-trained network is frozen without further updates. Instead, we decompose the matrices of the bypass network for fine-tuning which aims to achieve high precision while minimizing the number of trainable parameters.

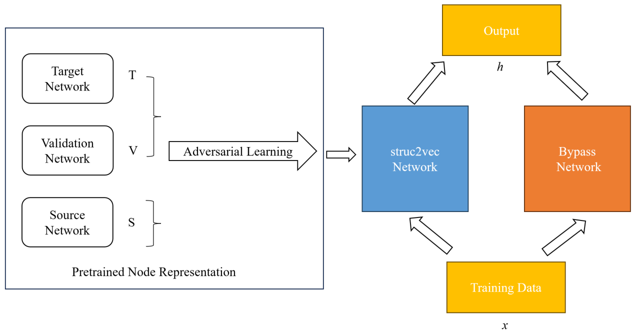

Fig.1 Framework for role discovery using LoRA

2.2 Generating Dateset

We will first validate our method on the four datasets used in the study [1]. The four datasets are toy network(combining four topology networks (mesh, ring, star, and tree), barbell graph dataset, Zachary's Karate Club dataset and air-traffic network dataset.

In the study [1], the dataset utilized for the topology networks appears rather simplistic. We intend to enhance our data collection efforts in this regard, gathering more complex datasets such as real-world social networks and transportation networks. As we broaden the complexity and diversity of the datasets, it may prompt further modifications to the networks we employ, aiming to deepen the existing models. The capabilities demonstrated by methods similar to LoRA in large-scale networks suggest that we should also lean towards selecting more complex models for our datasets. This approach will enable our method to fully leverage its capabilities and perform effectively.

2.3 Experiment

Our experimental design comprises four distinct groups. The first group utilizes our proposed method, employing training with a pre-trained network. In the second group, we enhance the previously trained stru2vec model by integrating LoRA which can be utilized after the transfer learning for further fine-tuning. The third group employs methods utilized in prior studies, while the fourth group utilizes the original stru2vec network.

3 Expected Result

Furthermore, our approach is expected to decrease the number of trainable parameters and train fatser while achieving improved performance compared to the target-tuned method. We anticipate that the accuracy will be notably enhanced, approaching the theoretical upper limit of neural networks. Looking ahead, in subsequent studies, when the neural network scales up, our method should prove even more efficient.

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