Fair Graph Representation Learning with Imbalanced and Biased Data

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ABSTRACT

Graph-structured data is omnipresent in various fields, such as biology, chemistry, social media and transportation. Learning informative graph representations are crucial in effectively completing downstream graph-related tasks such as node/graph classification and link prediction. Graph Neural Networks (GNNs), due to their inclusiveness on handling graph-structured data and distinguished data-mining power inherited from deep learning, have achieved significant success in learning graph representations. Nonetheless, most existing GNNs are mainly designed with unrealistic data assumptions, such as the balanced and unbiased data distributions while abounding real-world networks exhibit skewed (i.e., long-tailed) node/graph class distributions and may also encode patterns of previous discriminatory decisions dominated by sensitive attributes. Even further, extensive research efforts have been invested in developing GNN architectures towards improving model utility while most of the time totally ignoring whether the obtained node/graph representations conceal any discriminatory bias, which could lead to prejudicial decisions as GNN-based machine learning models are increasingly being utilized in real-world applications. In light of the prevalence of the above two types of unfairness originated from quantity-imbalanced and discriminatory bias, my research expects to propose novel node/graph representation learning frameworks through constructing innovative GNN architectures and devising novel graph-mining algorithms to learn both fair and expressive node/graph representations that can enjoy a favorable fairness-utility tradeoff.

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1 INTRODUCTION

Graph-structured data is ubiquitous in the real-world from various domains, such as chemistry, social media, transportation and linguistics [11]. Mining on graphs allows us to derive deeper insights and detect latent patterns, which are useful when paired with graph learning methods for completing graph-related prediction tasks such as node/graph classification [8] and link prediction [1]. As the generalization of deep learning to the graph domain, GNNs have become one of the most promising paradigms in learning informative graph representations [5, 9]. Despite the significant progress of devising avant-garde GNNs in learning expressive node/graph representations that can capture long-range dependencies or recognizing complex local topology contexts [2], the learned node representations have been demonstrated to be unfair because of imbalanced training quantity among different classes and sometimes even perpetrate undesirable discriminatory biases imposed by history data [3]. Therefore, studying the ability of GNNs in handling imbalanced data splitting that may cause quantitative unfairness or sensitive data that may cause attribute-based unfairness could impose significant enhancement and revolution on their practical usage; this research statement targets at these two aspects of GNNs: imbalanced classification and unbiased node representation learning. In the rest of this research statement, we will cover the related work and my previous/concurrent work with respect to both of the above two topics.

2 BACKGROUND AND RELATED WORK

Traditional methods for handling class imbalance have been primarily performed on simple point-based data and their performance on graph-structured data is significantly underexplored. For imbalanced node classification, nearly all existing GNNs reconstruct the graph topology by pre-training or adversarial training to balance the data instances [6, 12]. However, the computational load and the time complexity of the similarity calculation between all node pairs and pre-training the edge generator is rather heavy. For imbalanced graph classification, to the best of our knowledge, no work has been proposed yet under the framework of GNNs. Additionally, a plethora of studies have revealed that network data may include patterns of previous discriminatory decisions dominated by sensitive attributes such as gender, age and race, and the node representations learned by training GNNs on such data may explicitly inherit the existed societal bias and hence exhibit unfairness in downstream tasks [3]. The few existing works are proposed assuming only one sensitive attribute is presented while other seemingly innocuous features may be highly correlated with protected attribute, which will potentially cause model bias and left unattended by their methods.

3 IMBALANCED NODE CLASSIFICATION

Current GNNs are mostly proposed under the balanced data-splitting and hence directly employing them on imbalanced data would generate coarse representations of nodes in minority classes and ultimately compromise the classification performance. Therefore, we propose a novel Distance-wise Prototypical Graph Neural Network

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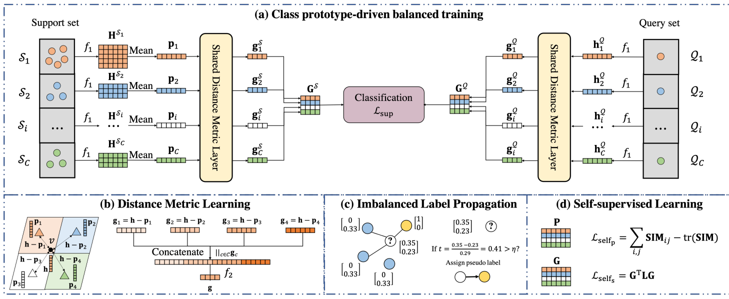

Figure 1: Overview of the proposed Distance-wise Prototypical Graph Neural Network (DPGNN), including four main components: (a) Class prototype-driven balanced training, (b) distance metric learning, (c) imbalanced label-propagation, and (d) self-supervised learning.

(DPGNN) [7] shown in Figure 1, which adopts a class prototype-driven training to balance the training loss between different classes and then leverages distance metric learning to differentiate the contributions of different feature channels and precisely encode the relative position of each node to each class prototype. Moreover, we design a new imbalanced label propagation mechanism to derive extra supervision from unlabeled nodes and employ self-supervised learning to smooth representations of adjacent nodes while separating inter-class prototypes.

4 IMBALANCED GRAPH CLASSIFICATION

Most existing graph classification problems with GNNs follow a balanced data splitting, which is misaligned with many real-world scenarios in which some classes have much fewer labels than others. Directly training GNNs under this imbalanced situation may lead to sub-optimal representations of graphs in minority classes, and compromise the overall performance of downstream classification, which signifies the importance of developing effective GNNs for handling imbalanced graph classification. To this end, we introduce a novel framework, Graph-of-Graph Neural Networks (G^2GNN) [10] shown in Figure 2, which alleviates the graph imbalance issue by deriving extra supervision globally from neighboring graphs and locally from graphs themselves. Globally, we construct a graph of graphs (GoG) based on kernel similarity and perform GoG propagation to aggregate neighboring graph representations, which are initially obtained by node-level propagation with pooling via a GNN encoder. Locally, we employ topological augmentation via masking nodes or dropping edges to improve the model generalizability in discerning topology of unseen testing graphs.

5 UNBIASED NODE REPRESENTATION LEARNING

Existing work has revealed that in graph-structured data, discriminatory decisions encoded by sensitive attributes maybe reflected further in the learned node representations and hence cause bias in downstream tasks [3]. Besides the sensitive attributes, network topology also serve as an implicit source to encode additional societal bias through proximity, e.g. nodes of similar sensitive attributes may lean towards connecting with each other due to network homophily as compared with those dissimilar ones. Such proximity-introduced bias by network topology could even be highlighted by message-passing schemes that are widely adopted in numerous

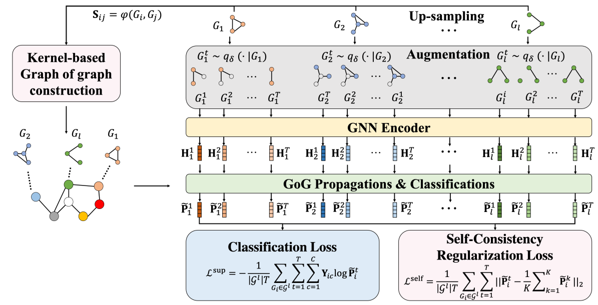

Figure 2: An overview of the proposed Graph-of-Graph Neural Network (G^2GNN) for imbalanced graph classification. Here we up-sample minority graphs to initially reduce the quantity-based imbalance effect, augment graphs T times followed by a GNN encoder to get their representations, aggregate neighboring graph representations by propagation on constructed GoG, and finally use their obtained logits for classification and the self-consistency regularization.

GNNs as feature aggregation smooths representations of adjacent nodes while separating distant ones', which further segregate nodes among different sensitive groups [3, 4]. Since sensitive information could be present in both sensitive attributes and their highly-correlated non-sensitive attributes, we propose a feature masker to automatically identify and cover feature channels that greatly contribute to the unfairness in learned node representations. Such feature masker would be trained jointly and adversarially with a sensitive group discriminator.

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