Fairness-aware Adaptive Network Link Prediction

O. Deniz Kose
Electrical Engineering and Computer Science
University of California Irvine
Irvine, USA
okose@uci.edu

Yanning Shen
Electrical Engineering and Computer Science
University of California Irvine
Irvine, USA
yannings@uci.edu

***Abstract*—Network link prediction has attracted increasing attention due to its capability of extracting missing information, and evaluating network-evolving mechanisms. Despite the increasing popularity, fairness is widely under-explored in the area. Motivated by this, this study proposes novel fairness-aware graph augmentation designs to mitigate the bias in graph data while creating node representations. Different fairness notions on graphs are introduced to guide the designs of the adaptive structural and attributive augmentation schemes. Experimental results on real-world networks demonstrate that the introduced augmentation frameworks can improve group fairness measures for link prediction while providing comparable utility to state-of-the-art contrastive learning algorithms.**

***Index Terms*—dynamic graphs, link prediction, fairness**

I. Introduction

Graphs are effective mathematical tools to represent and analyze diverse complex systems, e.g., biological networks [1], or financial markets [2]. This motivates the recent attention towards learning over graphs. Specifically, dynamic graphs are essential for modeling time-varying networks, which inspires various framework designs for them, see e.g., [3]–[6]. While dynamic graphs present certain challenges, graph neural networks (GNNs) have shown to be effective in learning complex relations within them for link prediction [7], node classification [8], source localization [9], and anomaly detection [10].

Link prediction is a task where the probability of the existence of a link between two nodes is estimated based on the input graph. Link prediction algorithms are capable of extracting missing information in networks and managing network-evolving mechanisms. A possible real-world application of such algorithms can be the recommender systems in social networks [11], [12], where the social circles of users are aimed to be enlarged via interesting suggestions for them. Therefore, the link prediction task is inherently related to the dynamic networks, where it can designate the evolution of networks, as well as be utilized to improve the learning models for them.

It has been shown that machine learning algorithms can give rise to discriminative results for certain underrepresented groups, as they propagate the bias within historical data on which they are trained [13]. Specifically, [14] demonstrates that the utilization of graph structure in learning can further amplify bias. For example, nodes in social networks connect to other nodes with similar attributes with higher probabilities, which results in denser connectivity between the nodes with the same sensitive attributes (e.g., gender, race) [15]. Thus, the node representations created by GNNs can be highly correlated with the sensitive attributes, as the representations are generated by aggregating information from the neighbors. Such a correlation occurs even when the sensitive attributes are not directly used in training [16]. Furthermore, specific to link prediction methods, bias can be reinforced over time due to the amplified segregation and narrowed diversity of objects, which is called filter bubble problem [17]. Amplified segregation is the result of promoted links between similar users (generally with similar sensitive attributes) based on the suggestions of the link prediction algorithm. For example, [18] demonstrates that there is a higher ethnic segregation in the relationships of Facebook users with more opportunities to meet similar others. Hence, the consideration of fairness is essential not to amplify the bias over time for link prediction algorithms.

While fairness-related literature is rich within the context of general machine learning, the field is rather under-explored for graphs. Adversarial regularization is a common strategy to mitigate the effects of sensitive attributes in the machine learning algorithms, which is also employed in fairness-aware link prediction studies [19], [20]. Furthermore, [21], [22] modify adjacency matrix to enhance different fairness measures specifically for link prediction, while [23] designs a regularizer for the same purpose. Fairness-aware pre-processing tools over graphs [24] can also be utilized to mitigate the bias in link prediction as the ensuing task. In this study, we present fairness-aware graph data augmentation strategies to reduce the bias within the graph structure and nodal features. Similar to the majority of the works mentioned above, the proposed schemes can be employed within the learning process as in-processing fairness tools. Additionally, our proposed strategies can be utilized as pre-processing tools on the input graph, which implies their applicability to different GNN-based learning frameworks in a versatile manner.

Contrastive learning methods maximize the agreement of representations that capture the dependencies of interest while creating embeddings in an unsupervised framework [25]. These methods have been shown to achieve the state-of-the-art results in various learning tasks over graphs such as node classification,

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regression, and link prediction [26]–[31]. In this work, the efficacy of the proposed augmentation for link prediction is evaluated within the framework of contrastive learning. Specifically, the learning framework of a graph contrastive learning study [29] is modified, where the fairness-unaware augmentation schemes utilized in [29] are replaced by adaptive fairness-aware strategies proposed in this work. Note that our previous work, [32], employs a similar learning framework specifically for node classification. Fairness-aware graph data augmentation is also utilized in [33] in order to create stable and fair representations. However, the augmentation introduced in [33] is not adaptive to the graph structure and designed primarily for counterfactual fairness. Furthermore, a biased edge dropout scheme is proposed in [34] to enhance fairness, that is said, the scheme therein again is not adaptive to the graph structure.

To sum up, this study introduces adaptive fairness-aware graph data augmentation strategies that can mitigate bias for link prediction. Overall our contributions can be summarized as follows:

c1) Based on graph-related fairness notions, novel adaptive augmentation strategies are introduced to mitigate potential bias. Compared to existing augmentation frameworks, the increase in the incurred computational complexity is negligible.

c2) Theoretical analysis is provided to demonstrate that the proposed adaptive augmentation on nodal features can effectively reduce intrinsic bias.

c3) Experimental results on real-world social networks demonstrate that the proposed schemes improve fairness metrics while providing comparable utility for link prediction compared to the state-of-the-art contrastive learning-based methods.

II. Fairness-aware Graph Data Augmentation

Graph topology augmentation is presented to improve the overall utility of the considered task by preventing overfitting issue in training [35]–[37]. Meanwhile, in the contrastive learning domain, graph data augmentation corrupts the graph structure and nodal features to create more robust representations to the applied augmentation, thus enhance utility in the ensuing tasks [26], [27], [29], [38]. Since the graph data presents unique challenges sourced from the dependent data samples, the design of augmentation for graphs is still a developing research area, although the field is extensively studied for tabular data. Both topological (e.g., edge/node deletion) and attributive (e.g., feature shuffling/masking) augmentation strategies are presented for graph contrastive learning [27]–[29], [38]. However, the presented corruption strategies so far are generally not adaptive to the input graph structure, i.e. treat each of the nodes (node deletion), edges (edge deletion), and features (feature masking) the same without considering graph connectivity. Although [38] and [28] introduce adaptive augmentation schemes, the motivation of these studies is to improve utility without any fairness consideration. This study proposes *fairness-aware* augmentation schemes both on the nodal features and graph topology to mitigate bias. Different from previous studies, the proposed strategies in this study are *adaptive* to the sensitive features of the nodes as well as the input graph structure.

A. Preliminaries

The focus of this study is the mitigation of bias in link prediction by creating fairness-aware node representations for a given graph $\mathcal{G} := (\mathcal{V}, \mathcal{E})$ in an unsupervised setting, where $\mathcal{V} := \{v_1, v_2, \cdots, v_N\}$ denotes the set of nodes and $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ is the set of edges. Nodal features and graph adjacency matrices of the input graph $\mathcal{G}$ are represented by $\mathbf{X} \in \mathbb{R}^{N\times F}$ and $\mathbf{A} \in \{0,1\}^{N\times N}$, respectively, where $\mathbf{A}_{ij} = 1$ if and only if $(v_i, v_j) \in \mathcal{E}$. A single, binary sensitive attribute for each node is considered herein, which is denoted by $\mathbf{S} \in \{0,1\}^{N\times 1}$. Overall, the main purpose is to learn a mapping $f : \mathbb{R}^{N\times N} \times \mathbb{R}^{N\times F} \times \mathbb{R}^{N\times 1} \rightarrow \mathbb{R}^{N\times F'}$ for the inputs $\mathbf{X}$, $\mathbf{A}$, and $\mathbf{S}$ in order to generate F' dimensional (generally $F' \ll F$) unbiased node representations $\mathbf{H} = f(\mathbf{A}, \mathbf{X}, \mathbf{S}) \in \mathbb{R}^{N\times F'}$, which will be employed in link prediction. The feature vector and the sensitive attribute of node v_i are denoted by $\mathbf{x}_i \in \mathbb{R}^F$ and $\mathbf{s}_i \in \{0,1\}$, respectively.

B. Fairness-aware Feature Masking

Even though feature masking is commonly utilized in the graph contrastive learning domain [28], [29], [33], [38], none of the previous masking schemes are fairness-aware. Motivated by this, this subsection presents a novel, *adaptive* feature masking strategy that creates corrupted nodal features $\tilde{\mathbf{X}}$ based on $\mathbf{X}$ to reduce intrinsic bias sourced from the nodal features.

It is shown in [16] that features that are correlated with the sensitive attributes propagate bias, even if the sensitive attributes are not directly used in the training. This finding motivates this work to consider sample correlation coefficient between the nodal features and sensitive attributes as a measure for possible bias introduced by the features. Specifically, the features that are highly correlated with the sensitive attributes are masked with larger probabilities to reduce the intrinsic bias. In the assignment of non-uniform feature masking probabilities, p-values [39] for two different sample correlation coefficient metrics are employed: the Pearson coefficient [40] and the Spearman coefficient [39]. Note that p-values reflect the likelihood of the uncorrelatedness of the data samples.

Overall, the adaptive feature mask $\mathbf{m}^{(f)} \in \{0,1\}^F$ is generated by drawing entries from a Bernoulli distribution for each feature with probabilities

$$p_i^{(f)} = p_i^{(c)}(1 - p^{(b)}), \quad i = 1, \ldots, F, \tag{1}$$

where $p_i^{(c)}$ is the p-value for the sample correlation coefficient between the ith feature and sensitive attributes $\mathbf{S}$, and $p^{(b)}$ is a hyperparameter determining the base masking probability. The masked/augmented feature matrix follows as

$$\tilde{\mathbf{X}} = [\mathbf{m}^{(f)} \circ \mathbf{x}_1; \ldots; \mathbf{m}^{(f)} \circ \mathbf{x}_N]^\top, \tag{2}$$

where $[\cdot;\cdot]$ corresponds to the concatenation operation, and $\circ$ is the Hadamard product.

To investigate the efficacy of the proposed masking scheme in reducing correlation, the total sample correlation is defined as $\rho = \sum_{i=1}^{F} |r_i|$, where r_i is the sample correlation coefficient between $\mathbf{x}_i$ and $\mathbf{S}$. Therefore, ρ is a measure of correlation between $\mathbf{X}$ and $\mathbf{S}$, which is desired to be reduced. ρ becomes a random variable together with the applied probabilistic masking strategy such that:

$$\rho := \sum_{i=1}^{F} R_i, \text{ with } R_i = \begin{cases} |r_i|, & \text{with prob. } \beta_i, \\ 0, & \text{with prob. } 1 - \beta_i, \end{cases} \tag{3}$$

where β_i is the probability that the i^{th} feature is not masked in the proposed augmentation. The following proposition showcases the superior strength of the proposed adaptive strategy over uniform feature masking in terms of reducing the expected value of ρ, the proof of which can be found in [32].

Proposition 1. *In expectation, the adaptive feature masking scheme presented in this study results in lower total sample correlation between the nodal features* $\mathbf{X}$ *and the sensitive attribute* $\mathbf{S}$ *compared to uniform feature masking, that is*

$$E_{\mathbf{p}^{(f)}}[\rho] \leq E_{\mathbf{q}}[\rho] \tag{4}$$

where $\mathbf{p}^{(f)} = [p_1^{(f)}, \cdots p_F^{(f)}]$ *with* $p_i^{(f)} = p_i^{(c)}(1 - p^{(b)})$ *corresponding to the proposed method and* $\mathbf{q} = [q_1, \cdots q_F]$ *with* $q_i = \frac{1}{F}\sum_{j=1}^{F} p_j^{(f)}$ *represents the uniform masking scheme.*

As ρ is a measure for the correlation, Proposition 1 implies the superior effectiveness of our approach in the reduction of intrinsic bias compared with the uniform feature masking scheme.

C. Fairness-aware Edge Deletion

Edge deletion is a graph topology augmentation, where a subset of edges are randomly deleted. While [14] demonstrates that the graph structure can propagate and amplify bias, none of the contrastive learning frameworks have considered a fairness-aware edge deletion strategy so far [28], [29], [31], [33], [38]. Motivated by this, this study proposes a fairness-aware edge deletion scheme that is adaptive to the input graph structure to create augmented graph topology $\tilde{\mathbf{A}}$ based on $\mathbf{A}$.

Due to the homophily principle, connections are tend to be formed between similar nodes in graphs [15]. For example, in social graphs, the number of edges between the nodes with the same sensitive attributes is mostly larger than the number of links between the nodes with different attributes (including all data sets utilized in this paper). Such a connectivity pattern results in the indirect utilization of sensitive attributes, as most of the neighbors whose information is aggregated in GNN-based learning have the same sensitive attributes. Thus, inspired by this bias propagation resulted from the graph connectivity, the following fairness concept is introduced:

$$p(\mathbf{A}_{ij} = 1 | s_i = s_j) = p(\mathbf{A}_{ij} = 1 | s_i \neq s_j). \tag{5}$$

Equation (5) aims to make the probabilities of the existence of an edge between two nodes v_i and v_j independent of the sameness of their sensitive attributes.

Following the fairness notion in (5), present adaptive edge deletion scheme assigns different edge deletion probabilities based on the sameness of the sensitive attributes that the corresponding edges connect. Let $|E_s|$ and $|E_d|$ denote the cardinalities of the edge sets including the edges between the same and different sensitive attributes, respectively. The adaptive edge deletion probabilities are assigned as

$$p^{(e)}(e_{ij}) = \begin{cases} 1 - p^{(\kappa)}, & \text{if } s_i \neq s_j \\ 1 - \frac{|E_d|}{|E_s|} p^{(\kappa)}, & \text{if } s_i = s_j, \end{cases} \tag{6}$$

where $p^{(e)}(e_{ij})$ is the probability that the edge between nodes v_i and v_j is deleted, $p^{(\kappa)}$ is the probability that the edges linking different sensitive attributes are not deleted.

III. Fairness-aware Link Prediction via Contrastive Learning

The contrastive loss utilized in this study maximizes the node-level agreement, i.e., the representations of the same nodes created under two different corrupted graph views are aimed to be discriminated from the embeddings of other nodes [29]. The corrupted graph views, $\widetilde{G}^1$ and $\widetilde{G}^2$, are generated via the fairness-aware adaptive augmentation strategies proposed in this study. The node representations generated with these views are denoted by $\mathbf{H}^1 = f(\widetilde{\mathbf{A}}^1, \widetilde{\mathbf{X}}^1)$ and $\mathbf{H}^2 = f(\widetilde{\mathbf{A}}^2, \widetilde{\mathbf{X}}^2)$, where $\widetilde{\mathbf{A}}^i$, and $\widetilde{\mathbf{X}}^i$ are the augmented adjacency and feature matrices of the graph view $\widetilde{G}^i$.

Let $\mathbf{h}_i^1$ and $\mathbf{h}_i^2$ be the representations for node v_i, then a node-level agreement means that $\mathbf{h}_i^1$ and $\mathbf{h}_i^2$ are more similar to each other than to the representations of all other nodes. Therefore, in the utilized contrastive learning loss, the embeddings of all nodes v_j where $i \neq j$ are used as negative examples for the representation of node v_i. Overall, considering $\mathbf{h}_i^1$ as the anchor representation, the utilized contrastive loss follows as:

$$\ell\left(\mathbf{h}_i^1, \mathbf{h}_i^2\right) = \\ - \log \frac{e^{s\left(\mathbf{h}_i^1, \mathbf{h}_i^2\right)/\tau}}{e^{s\left(\mathbf{h}_i^1, \mathbf{h}_i^2\right)/\tau} + \sum_{k=1}^{N} 1_{[k \neq i]} e^{s\left(\mathbf{h}_i^1, \mathbf{h}_k^2\right)/\tau} + \sum_{k=1}^{N} 1_{[k \neq i]} e^{s\left(\mathbf{h}_i^1, \mathbf{h}_k^1\right)/\tau}} \tag{7}$$

where $s\left(\mathbf{h}_i^1, \mathbf{h}_i^2\right) := c\left(g(\mathbf{h}_i^1), g(\mathbf{h}_i^2)\right)$, with $c(\cdot, \cdot)$ standing for the cosine similarity between the input vectors, and $g(\cdot)$ implemented by using a 2-layer multi-layer perceptron (MLP) [29]. Parameter τ denotes the temperature hyperparameter, and $1_{[k \neq i]} \in \{0, 1\}$ is the indicator function which is equal to 1 when $k \neq i$. If $\mathbf{h}_i^2$ is considered as the anchor example, then a symmetric version of this loss can also be written, which results in the following final loss:

$$\mathcal{J} = \frac{1}{2N} \sum_{i=1}^{N} \left[\ell\left(\mathbf{h}_i^1, \mathbf{h}_i^2\right) + \ell\left(\mathbf{h}_i^2, \mathbf{h}_i^1\right) \right]. \tag{8}$$

Upon obtaining node representations $\mathbf{H}$ with a model trained using the loss in (8), link prediction is executed with a linear classifier based on l_2-regularized logistic. The inputs to this classifier are the concatenated representations of the nodes that the corresponding edges connect (i.e., $[\mathbf{h}_i; \mathbf{h}_j]$ for edge e_{ij}),

	UCLA26			Oklahoma97			Berkeley13		
	Accuracy (%)	Δ_{SP} (%)	Δ_{EO} (%)	Accuracy (%)	Δ_{SP} (%)	Δ_{EO}(%)	Accuracy (%)	Δ_{SP} (%)	Δ_{EO}(%)
GRACE [29]	70.64 ± 0.65	1.02 ± 0.89	2.44 ± 1.10	72.29 ± 0.17	6.61 ± 0.19	1.33 ± 0.86	69.08 ± 0.23	1.01 ± 0.47	3.51 ± 1.33
GCA [38]	$\mathbf{70.70} \pm 0.55$	0.78 ± 0.73	2.49 ± 0.73	72.22 ± 0.11	6.25 ± 0.58	0.84 ± 0.46	$\mathbf{69.24} \pm 0.24$	0.82 ± 0.47	4.17 ± 0.97
NIFTY [33]	70.53 ± 0.19	0.75 ± 0.61	2.80 ± 0.60	72.30 ± 0.13	6.20 ± 0.50	0.76 ± 0.35	69.12 ± 0.29	0.84 ± 0.63	3.63 ± 1.51
FM + ED	70.54 ± 0.39	$\mathbf{0.61} \pm 0.88$	$\mathbf{2.15} \pm 0.89$	$\mathbf{72.32} \pm 0.17$	6.37 ± 0.63	$\mathbf{0.69} \pm 0.53$	69.18 ± 0.51	0.81 ± 0.77	$\mathbf{3.47} \pm 1.09$
FM	70.61 ± 0.73	1.08 ± 1.28	2.30 ± 1.24	72.12 ± 0.22	$\mathbf{6.14} \pm 0.32$	0.84 ± 0.61	68.99 ± 0.35	$\mathbf{0.74} \pm 0.71$	4.03 ± 1.74
ED	70.56 ± 0.62	0.95 ± 1.05	2.21 ± 1.44	72.19 ± 0.20	6.33 ± 0.25	1.15 ± 0.77	69.17 ± 0.20	0.84 ± 0.54	4.03 ± 0.79

TABLE I: Comparison of proposed feature masking (FM) and edge deletion (ED) schemes with baselines on Facebook networks.

and the outputs are the binary labels indicating whether the edges exist or not (i.e. $y_{ij} = 1$ if $e_{ij} \in \mathcal{E}$, $y_{ij} = 0$ otherwise).

IV. Experiments

This section presents experiments over three real-world networks for link prediction.

Datasets: Experiments are conducted on three Facebook networks: UCLA26, Oklahoma97, and Berkeley13 [41]. In these graphs edges are generated based on the friendship information in social media. Each user (node) has 7 dimensional nodal features consisting of student/faculty status, gender, major, etc. Gender is used as the sensitive attribute in the experiments.

Performance metrics: Accuracy of link prediction is utilized as the utility measure in the experiments. As the fairness metrics, the definitions of statistical parity and equal opportunity are adapted [21] for link prediction such that $\Delta_{SP} = |P(\hat{y} = 1 \mid e \in \mathcal{E}^{\chi}) - P(\hat{y} = 1 \mid e \in \mathcal{E}^{\omega})|$ and $\Delta_{EO} = |P(\hat{y} = 1 \mid y = 1, e \in \mathcal{E}^{\chi}) - P(\hat{y} = 1 \mid y = 1, e \in \mathcal{E}^{\omega})|$, where e represents the edges and $\hat{y}$ is the prediction for whether the edge exists.

Experimental settings: For a fair comparison, the contrastive learning framework is kept the same as the one employed in [29]. The overall results are generated by shuffling the data 4 times and taking the average of the results. For more details on the experimental setup of proposed augmentation, see [32].

Baselines. Our natural baseline is GRACE [29] where the non-adaptive augmentation schemes used in [29] are replaced with our proposed fairness-aware adaptive augmentation. Furthermore, GCA [38] is also used as a baseline, which is another study built upon [29] for improving utility. Finally, NIFTY [33] is employed as the fairness-aware baseline study, which is also the only contrastive learning study considering fairness to the best of our knowledge.

Results. Table I lists the results of the proposed adaptive feature masking (FM) and edge deletion (ED) strategies together with the results of baselines. First, the results in Table I demonstrate that the employment of proposed FM together with ED generally improves the overall fairness metrics together with similar prediction accuracy values. Therefore, the employment of proposed FM and ED schemes together is a better strategy for fairness improvement, which can support our claim that both graph topology and nodal features propagate bias.

The graph contrastive learning schemes GRACE [29], GCA [38], NIFTY [33]) all employ both feature masking and edge deletion to corrupt input graphs, which makes them natural baselines for the proposed FM+ED strategy. Specifically, as the experimental results are obtained by replacing the augmentation schemes in GRACE with the proposed strategies herein, a performance comparison with GRACE can show solely the effects of the proposed augmentation schemes. Table I shows that the proposed augmentation methods result in better fairness measures together with similar link prediction accuracy compared to GRACE, which showcases the effectiveness of the proposed fairness-aware augmentation designs.

The results in Table I demonstrate that NIFTY outperforms our proposed FM+ED strategy on Oklahoma in terms of Δ_{SP}, while our scheme is better than NIFTY in terms of Δ_{EO}. However, results further show that our proposed FM+ED scheme performs better than NIFTY [33] both on UCLA26 and Berkeley13 in terms of both fairness metrics. Therefore, the overall superior fairness performance of our method compared to NIFTY can indicate that the focus on counterfactual fairness in NIFTY may limit its efficacy for improving other fairness metrics.

Finally, GCA is built upon GRACE via adaptive augmentation designs aiming to improve the utility. As the proposed adaptive augmentation strategies of GCA are not fairness-aware, their effects on fairness are not predictable, which is also shown by the results in Table I. Overall, the proposed fairness-aware strategies generally lead to better fairness metrics than other state-of-the-art graph contrastive learning methods, with similar link prediction accuracy.

V. Conclusion

This study presents adaptive, fairness-aware graph data augmentation strategies for both graph structure and nodal features to mitigate bias in link prediction. Experimental results for the proposed schemes show that the proposed fairness-aware designs can enhance fairness measures while providing comparable link prediction accuracy to the state-of-the-art. While the proposed schemes can be employed in the learning process as in-processing fairness tools, they can also be utilized as pre-processing tools on the input graph. The present work opens up several intriguing future directions: i) extension of the present work to the cases where there exist multiple sensitive attributes; ii) more extensive experimental results for the proposed framework, when it is employed as a pre-processing tool on different GNN-based learning schemes other than contrastive methods.

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