Research Proposal

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1 Introduction

In recent years, graph mining has been widely used to understand rich information hidden in graphs. Graph Neural Networks (GNNs) have emerged as state-of-the-art for graph mining and show impressive performance in various real-world applications, e.g., healthcare [1, 2], bioinformatics [3, 4] and recommender systems [5, 6], to name a few.

To deal with the need for a huge number of graph data and the regularization of user privacy [7] when training GNN models, Federated Graph Machine Learning (FGML) [8, 9] is proposed. FGML is a distributed machine learning scheme that trains a graph model across different participating devices/silos without sharing private data. While providing a promising paradigm, FGML faces several challenges in realistic scenarios. For example, residents of a city may go to different banks for various reasons. Their personal data, such as demographics, income conditions, and transaction activities (interactions) can be collected by bank branches. When approving loan requests, a central bank administration (or central server) can utilize a graph model trained on the entire bank network to evaluate better if a loan applicant is benign. However, due to conflicts of interest, a bank may reluctant to share its user networks with others. Thus, the first challenge is that the local subgraphs collected from different devices/silos are limited and may miss critical information. What's worse, a graph model trained on the corrupted network plus the bias introduced by devices/silos selection [10] could lead to undesired discrimination against users from certain demographic subgroups (e.g., age, gender, and race) and would mistakenly reject a loan of a user that belongs to an underprivileged group. As a result, how to alleviate the bias in FGML is another challenge.

As an attempt to address the challenges, we propose an FGML framework named **EGRESS** (f**E**derated **G**ene**R**ativ**E** GNN with **S**tructural debia**S**ing). The overall structure is shown in Fig.1. Firstly, to deal with the challenge of missing information (e.g., node and feature) across local subgraphs, we collaboratively train a **Generator Module** to generate missing neighbors as well as features for nodes on each subgraph and form an augmented local subgraph. Specifically, each subgraph first holds out some nodes and trains the generator based on the held-out neighbors. The gradients of the generator are then aggregated with ones on other subgraphs in a federated fashion. The output augmented graph is later fed into a local GNN model trained with FedAvg [8]. In addition, to tackle the second challenge, we propose a **Dibiasing Module** where we use a debiasing strategy with the help of GNNExplainer [11]. To be more specific, we employ a Bias Explainer to identify edges that maximally account for the exhibited node-level bias given a node's computation graph in a device/silo. Similarly, another Fairness Explainer can be defined by identifying the edges whose presence can maximally alleviate the node-level bias. We employ a sensitive bias metric based on Wasserstein distance [12] in the probabilistic outcome of GNN prediction since the probabilistic space can better preserve the exhibited bias [13, 14].

2 Problem Setup

Preliminaries. We mainly focus on cross-silo FGML in this proposal. Let $D = \{d_1, d_2, ..., d_m\}$ be

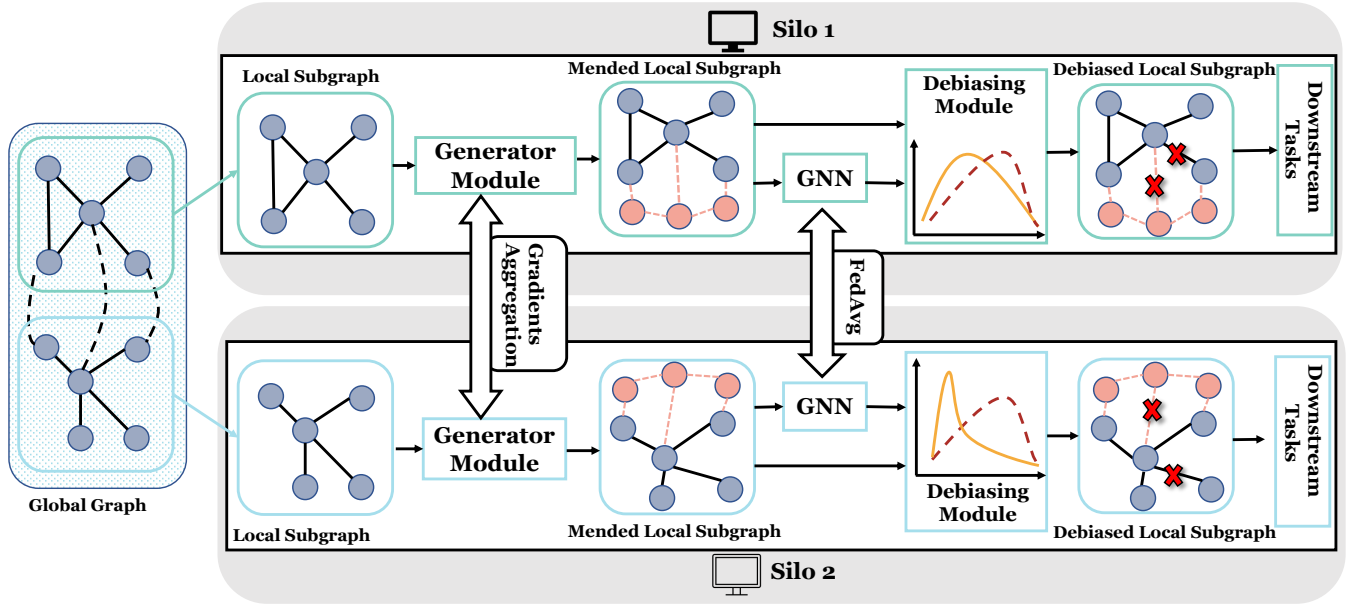


Figure 1: Overall Structure of EGRESS

a set of M data owners. We denote a global graph as $G = \{V, E, X\}$, where $\{V\}$ is the node set, $\{X\}$ is the corresponding node feature set, and E is the edge set. Under the FGML system, we have a central server S to conduct Gradients Aggregation as well as FedAvg, and M data owners with their corresponding local subgraph $G_i = \{V_i, E_i, X_i\}, \forall i \in [D]$. In addition, any data owner D_i cannot directly retrieve data from another data owner D_j. We assume $V = V_1 \cup V_2 \cup ... \cup V_M$. Besides, we have missing edges existing in reality but not stored in the whole system. Specifically, for an edge $e_{v,u} \in E$, where $v \in V_i, u \in V_j$ and $e_{v,u} \notin (E_i \cup E_j)$ (shown as the dash line in GlobalGraph in Fig. 1).

Goal. We mainly focus on node classification. The goal of the proposed framework is to collaboratively learn on isolated subgraphs in all data owners, without raw graph data sharing, to obtain a global graph mining model (e.g., GNN) [15]. For the global graph $G = \{V, E, X\}$, every node $v \in V$ has its feature $x_v \in X$ and label $y_v \in Y$ which is a d_y-dimensional one-hot vector.

3 Proposed Method

In this section, we first present the methodology to train the **Generator Module**, which can generate mended subgraphs under the FGML system. Secondly, we demonstrate how to address the bias introduced by the FGML system and mended subgraphs with the **Debiasing Module**.

3.1 Generator Module

To deal with the challenge of missing node and feature across local subgraphs, we proposed a Generator Module. For each silo, we have a Generator Module including a multi-layer GNN encoder H^e and a generative model H^g.

H^e. The output of our GNN encoder is the embeddings for nodes, $Z_i = \{z_v | z_v \in \mathbb{R}^{dz}, v \in V_i\}$.

H^g. For each silo, we feed the output of the GNN encoder Z_i into the generative model. It contains a MLP, H_1^g, that aims to predict the numbers of missing neighbors for each node $\widetilde{N} = \{\widetilde{n}_v | \widetilde{n}_v \in \mathbb{N}, v \in V_i\}$, and another MLP, H_2^g, that generates a set of $\widetilde{N}$ feature vectors $\widetilde{X}_i = \{\widetilde{x}_v | x \in \mathbb{R}^{\widetilde{n}_v \times d_x}, \widetilde{n}_v \in \widetilde{N}, v \in V_i\}$.

Objective Function. To train the Generator Module, we first randomly hold out $h\%$ of nodes $V_i^h \subset V$ and corresponding edges and features in the local subgraph G_i, denoted as $\overline{G}_i = \{\overline{V}_i, \overline{E}_i, \overline{X}_i\}$, where $\overline{V}_i$, $\overline{E}_i$ and $\overline{X}_i$ is the impaired node set, edge set, and feature set, respectively. Thus H_1^g can be optimized by

$$L_g^1 = \frac{1}{|\overline{V}_i|} \sum_{v \in \overline{V}_i} L_1^S(\widetilde{n}_v - n_v),$$

where L_1^S is the smooth L1 distance [16]. Then, H_2^g can be jointly optimized by Gradients Aggregation [17]. Specifically, for node $v \in \overline{V}_i$, we ensure that the generated features in silo i and j should be close to the feature of v's hided neighbor. Thus, mathematically, H_2^g can be trained with

$$L_g^2 = \frac{1}{|\overline{V}_i|} \sum_{v \in \overline{V}_i} \sum_{p \in [\widetilde{n}_v]} \Big(\min_{u \in \mathbf{N_{G_i}}(v) \cap V_i^h} (||\widetilde{x}_v^p - x_u||) + \alpha \sum_{j \in [M] \setminus i} \min_{u \in V_j} (||H_2^g(z_v)^p - x_u||) \Big),$$

where $\mathbf{N_{G_i}(v)}$ is the neighbor of node v in the local graph G_i and the feature of node $u \in \mathbf{N_{G_i}(v)} \cap \mathbf{V_i^h}$ provides ground truth for the generated feature in the first term $min_{u \in \mathbf{N_{G_i}}(v) \cap V_i^h}(||\widetilde{x}_v^p - x_u||)$. In addition, the model gradients of loss term $\sum_{j \in [M]/i} min_{u \in V_j}(||H_2^g(z_v)^p - x_u||)$ can be calculated from silo D_j. Finally, the gradients are weighted by α and aggregated by silo D_i.

Based on the Generator Module, we feed the mended graph into a GNN model that can be trained by FedAvg in FGML. Thus, the Generator Module and a GNN classifier can be jointly trained by

$$L = \lambda_1 L_c + \lambda_2 L_g^1 + \lambda_3 L_g^2,$$

where L_c is a cross-entropy loss of the GNN model for node classification, and $\lambda_1, \lambda_2, \lambda_3$ are hyperparameters.

Table 1: Dataset Statistics.

	Global Graph	Silo1	Silo2	Silo3
#V	1000	367	254	379
#E	24970	7150	4911	7649

Table 2: Results on Performance.

	Accuracy	ROC-AUC
GlobalGraph	0.7040	0.7388
LocalGraph1	0.6892	0.7114
LocalGraph2	0.6965	0.6670
LocalGraph3	0.6940	0.6604
FedGNN	0.6985	0.7001
EGRESS	0.7025	0.7339

3.2 Debiasing Module

To alleviate the bias introduced by the generative model [18] and the Federated Learning system [19], also to get a more fair result, we utilize a node-level Debiasing Module that includes a Bias Explainer and Fairness Explainer inspired by GNNExplainer. The output of this module is the debiased local subgraph as shown in Fig.1. Please note that for simplicity we ignore the silo notation for the following sections.

Objective Function. We use $\hat{Y}$ to represent the outcome of the GNN model in a silo, and $\widetilde{y}_i$ to represent the probabilistic outcome of the GNN model with fixed parameters based on the computation graph G_c^i for node v_i. We replace $\hat{y}_i$ in the GNN outcome with $\widetilde{y}_i$, and the outcome set can then be denoted as $\widetilde{Y}$, e.g., $\widetilde{Y} = \hat{Y} \backslash \{\hat{y}_i\} \cup \{\widetilde{y}_i\}$. We then split $\widetilde{Y}$ into two sets based on the sensitive group (e.g., gender) as $\widetilde{Y}_0$ and $\widetilde{Y}_1$, also the corresponding distribution is $P(\widetilde{Y}_0)$ and $P(\widetilde{Y}_1)$. If $\hat{y}_i$ is replaced, then the distribution distance between the two sensitive subgroups will also be changed accordingly. Thus, the Biased Explainer aims to derive $\widetilde{y}_i$ that can maximize the distribution distance between $P(\widetilde{Y}_0)$ and $P(\widetilde{Y}_1)$.

Table 3: Results on Fairness.

	Wasserstein Distance	Wasserstein Distance'	Statistical Party	Equal Opportunity
GlobalGraph	0.1487	0.1386	0.0309	0.0106
Silo1	0.3901	0.3822	0.0481	0.0659
Silo2	0.2221	0.2199	0.0491	0.0849
Silo3	0.2867	0.2842	0.0338	0.0447

This can be achieved by training a mask to identify edges $\widetilde{E}_i$ in the computation graph of node v_i, and $\widetilde{E}_i$ are supposed to lead to a larger distribution distance. Thus, the objective of the Biasd Explainer based on Wasserstein-1 distance (W1) as

$$\max_{\widetilde{E}_i} W1(P(\widetilde{Y}_0), P(\widetilde{Y}_1)),$$

where $\widetilde{E}_i$ is the edge set given by Bias Explainer. We adopt a common-used approximation strategy [20, 14] to optimize Wasserstein-1 distance with SGD. Similarly, the goal of Fairness Explainer is to train another mask to identify an edge set $\widetilde{E}'_i$ in the computation graph of node v_i, and $\widetilde{E}'_i$ can minimize the distribution distance. Thus, by following the similar method of Bias Explainer, $\widetilde{y}'_i$ is derived from the Fairness Explainer based on its computation graph $G_c^{i\prime}$, and $P(\widetilde{Y}'_0)$ and $P(\widetilde{Y}'_1)$ denote the distribution of two sensitive groups by replacing $\hat{y}_i$ with $\widetilde{y}'_i$, ($\widetilde{Y}' = \hat{Y} \backslash \{\hat{y}_i\} \cup \{\widetilde{y}'_i\}$). Therefore, we demonstrate the goal of the Fairness Explainer as

$$\min_{\widetilde{E}'_i} W1(P(\widetilde{Y}'_0), P(\widetilde{Y}'_1)),$$

Based on the above methods, the two Explainers can be jointly optimized with

$$L_e = W1(P(\widetilde{Y}'_0), P(\widetilde{Y}'_1)) - W1(P(\widetilde{Y}_0), P(\widetilde{Y}_1)).$$

Apart from that, the two explanations given by Bias and Fairness Explainers should incorporate the critical information of the original prediction $\hat{Y}_i$. This constraint can be achieved by maximizing the mutual information [11] between the corresponding computation graph $\widetilde{G}_c^i / \widetilde{G}_c^{i\prime}$ and $\hat{Y}_i$:

$$L_m = -\mathbb{E}_{\hat{Y}_i|\widetilde{G}_c^i}[logP_\Theta(\hat{Y}_i|\widetilde{G}_c^i)] - \mathbb{E}_{\hat{Y}_i|\widetilde{G}_c^{i\prime}}[logP_\Theta(\hat{Y}_i|\widetilde{G}_c^{i\prime})].$$

Thus, the two explainers can be jointly trained by

$$L = \lambda_4 L_e + \lambda_5 L_m + \lambda_6 L_r,$$

where $\lambda_4, \lambda_5, \lambda_6$ are hyperparameters and L_r is the regularization term to ensure the sparsity of the masks of the two explainers.

3.3 Debiasing Subgraph

In this section, we aim to alleviate bias on each subgraph with the instance-level explainers given by the Debias Module. The rationale is that the fairness of a GNN's prediction can be promoted by reducing node-level bias. This intuition also aligns with existing works [21, 14, 22]. However, only removing edges that tend to introduce bias in the outcome of a GNN model might lead to erasing some critical edges for the model performance (e.g., GNN Prediction). Similarly, it is neither reasonable to merely preserve edges found by Fairness Explainer since other unselected edges may contribute to the prediction result of other nodes. As a consequence, we first sample some nodes from each Mended Local Subgraph. And then we remove edges in the edge set $\widetilde{E}_i$ given by the Bias Explainer but not in the explanation $\widetilde{E}'_i$ from the Fairness Explainer. Eventually, the bias in the Mended Local Subgraph can be alleviated, and the corresponding output is a Debiased Local Graph, as shown in Fig.1.

4 Experiments

In this section, we demonstrate the experiments of our proposed framework on the graph classification task. We first introduce settings, and then the experimental results.

4.1 Experimental Settings

Dataset. We mainly focus on the German Credit dataset. Nodes and edges represent the bank clients and the connections between client accounts, respectively. To simulate the scenario of FGML, we cut the graph of German Credit into three silos (from silo1 to silo3) with Louvain algorithm [23]. The statistics of the dataset are shown in Table 1, where $\#V$ means the number of nodes and $\#E$ means the number of edges.

Evaluation Metrics. We use four metrics in the experiments. **Accuracy** and **ROC-AUC** can be used to gauge the model performance. The node-level bias can be measured by **Wasserstein-1 distance**, the lower, the better. **Statistical Party** [24] and **Equal Opportunity** [25] are two traditional fairness metrics.

Implementation Details. We adopt the split rate for the training set and validation set as 0.8 and 0.1 in the training of Generator Module and Debiasing Module. In the training of the Generator Module, we set the training epochs as 20. We use 1×10^{-3} as the learning rate and 10 for feature size. We set λ_1, λ_2 and λ_3 as 1. We use hidden portion $h = 0.5$. In addition, we set $\delta = 50$ as the number of missing links while splitting the GlobalGraph into each silo. The coefficient of gradients aggregation α is 1. For the training of the Debias Module, we use GNNExplainer as the backbone of the two explainers. The learning rate is 0.5 and the training epoch is 20. In addition, we set $\lambda_4 = 1, \lambda_5 = 1e-4$ and $\lambda_6 = 1e-4$. We sample 10% of nodes in each silo for debiasing.

4.2 Experimental Results

4.2.1 Framework Performance

The preliminary experimental results on model performance are demonstrated in Table 2. LocalGraph1-3 denote the proposed Generator Module training on each local graph without Gradients Aggregation and FedAvg strategies. FedGNN is built on a GNN classifier by employing FedAvg. These are set as baselines for model performance. The row of GlobalGraph means the result is calculated on the graph that is not split into different parts. It sets the upper bound of the experiment. We can observe that our proposed framework outperforms FedGNN and all LocalGraph models thanks to the Generator Module with Gradients Aggregation. In addition, compared with the result of GlobalGraph, EGRESS achieves comparable performance.

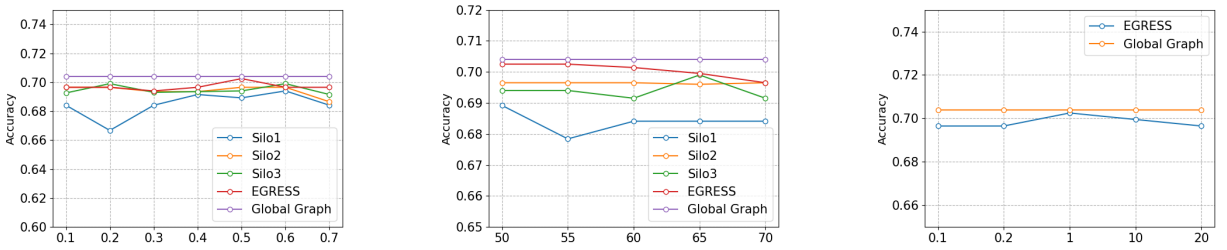
4.2.2 Framework Fairness

We conduct experiments to verify the important promotion of Fairness brought by EGRESS. The results are shown in Table 3, where Silo1-Silo3 of column **Wasserstein Distance** denotes the bias of prediction results before the Debiasing Module of EGRESS, while **Wasserstein Distance'** shows the node-level bias after the Debiasing Module. We have the following observation emerging from the results:

- From column **Wasserstein Distance**, compared with the result of GlobalGraph, the FGML system and the generative model definitely introduce node-level bias, which proves the necessity of our Debiasing Module.
- From **Wasserstein Distance'**, the reduction of node-level bias can be observed in GlobalGraph and all silos. This indicates that our proposed Wasserstein distance-based objective functions effectively help to alleviate the exhibited bias by incorporating the two explainers.
- **Statistical Party** and **Equal Opportunity** also demonstrate the node-level bias after our Debiasing Module. The comparable results can be observed with respect to **Statistical Party**. However, we still have room to improve on the metric of **Equal Opportunity**.

4.2.3 Hyperparameter Analysis

In this section we conduct the hyperparameter analysis of the proposed framework. Regarding the performance of EGRESS, we explore the Hidden Portion, h, of nodes while training Generator Module, the number of missing cross-subgraph links, δ, while assigning subgraphs to each silo, and the coefficient α of Gradients Aggregation. The results based on Accuracy are reported, as we witness the same trend on



(a) Hidden Portion (b) # Missing Cross-Subgraph Links (c) Coefficient of Gradients Agg.

Figure 2: Hyperparameter Analysis w.r.t. Performance.

ROC-AUC. We have the following observations from Fig.2.

- Fig.2(a) indicates either too small or too large hidden portion of nodes when training the Generator Module can degrade the framework performance. A small hidden proportion leads to insufficient data for training the Generator Module, while a large one makes the subgraph in each silo sparse.
- Referring to Fig.2(b), our proposed model is robust regarding missing links. This is because EGRESS can generate missing links to reduce the influence of missing data.
- The coefficient of Gradients Aggregation α measures how much information will be brought from other silos. From 2(c), it shows the robustness of the Gradients Aggregation method. In general, even though our framework is not sensitive to hyperparameters, the performance can still benefit from proper fine-tuning.

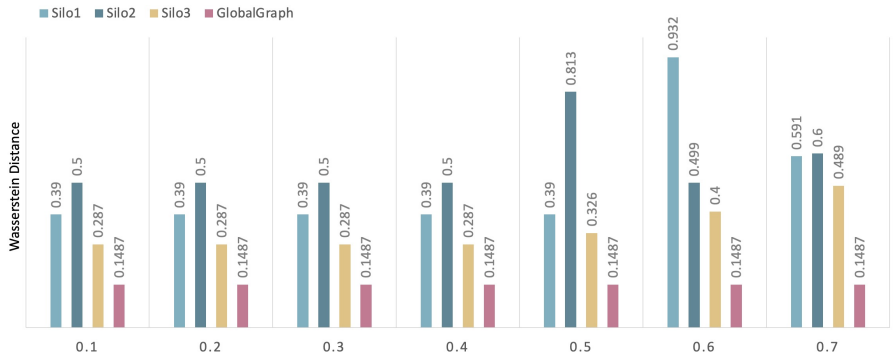
We then explore the results on fairness with Hidden Portion h and the number of missing cross-subgraph links δ. The outcome is shown in Fig.3.

- Fig.3(a) demonstrates that with more nodes being hidden, the Wasserstein Distance fluctuates significantly. This is because the sparse subgraph on each silo resulting from a large hidden portion can impact the output of the Generator Module and lead to undesired bias in the Mended Local subgraph. This implies the need for our Debiasing Module.
- The number of missing cross-subgraph links simulates the scenario of lacking critical information while splitting the GlobalGraph into different silos. As shown in Fig.3(b), more bias is introduced to the prediction results of each data instance as the amount of missing links becomes larger. This also aligns with our non-trivial discussion that limited information in silos under an FGML system shows distinct bias against some groups of data (e.g., gender).

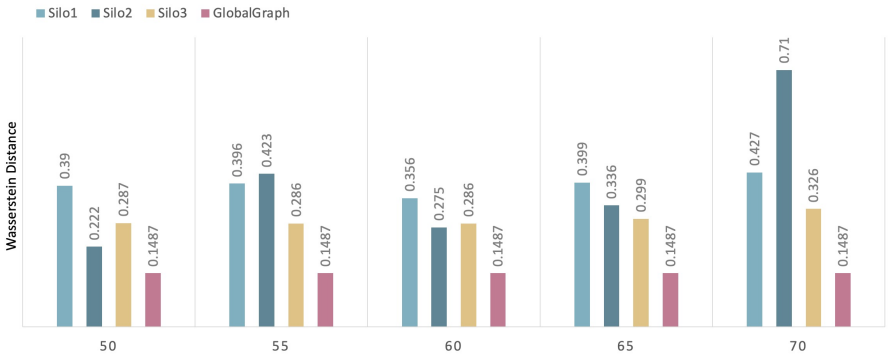
5 Future Works

In this section, I present my thoughts on future works inspired by the experiments.

- **Framework.** The framework can be further refactored in the future. The Generator Module is originally proposed to deal with problems in the medical area, thus, we could redesign the framework to make it fit our scenario. In addition, this framework contains codes based on both Pytorch and TensorFlow. We are not sure if the fuse of these two libraries can cause the degradation of performance. Thus, it is necessary to modify the framework in a unified way as it benefits both code sharing and future experiments.



(a) Hidden Portion



(b) # Missing Cross-Subgraph Links

Figure 3: Hyperparameter Analysis w.r.t. Bias.

- **Data Heterogeneity.** When I conducted the experiments, I observed that the performance as well as the node-level bias highly depend on the data on each silo (e.g., node and edge number). If the data gap is huge, for example, one silo contains 100 nodes but another 500, the results will degrade so much. More research on dealing with heterogeneous data while assuring fairness is needed.

- **Generative Model.** To deal with the data heterogeneity, from my perspective, we can resort to generative models. Also the appearance of diffusion models [26, 27] on CV area provides us a powerful way to utilize probabilistic generative models. In addition, a generative model may output similar features for multiple nodes, preventing us from generating diverse neighbors for a node, especially in an FGML scenario. Thus, tackling this problem is one thing we can explore.

- **Trustworthy FGML.** In our framework, the debiasing strategy is not trained with a Federated Learning fashion, since in my opinion, we want to acquire a mask tailored for each silo. It makes no sense to aggregate bias information from other silos. However, there might be other ways to maintain fairness in FGML, e.g., try other fairness notions apart from group fairness.

6 Related Work

In this section, we review some related works from two folds, including the Fairness of GNNs and Fed-

erated Graph Machine Learning.

Fairness of GNNs. Various studies have investigated the Fairness of GNNs. There are two types of fairness most commonly discussed: group fairness[24] and individual fairness[28]. Group fairness requires that demographic subgroups are treated equally by GNNs [29, 30]. Adversarial learning is one of the most popular debiasing approaches aiming to learn less biased node representations that fool the discriminator[31, 32]. Fair representation can be seen as achieved when the discriminator can hardly distinguish the sensitive feature given any learned node representations. Moreover, from the perspective that biased prediction stems from unfair connections in the graph structure or biased node features, fair graph methods are proposed. These methods aim to modify graph structure [33] or node features [34] before or during the training of GNNs. On the other hand, Individual fairness requires that similar individuals obtain similar predictions from GNNs[35, 28]. Based on the Lipschitz property[24], [35] refines the definition of individual fairness for graph mining and utilizes similarity-weighted output discrepancy between nodes to measure unfairness. Another line of research fulfills the goal from a ranking perspective[36]. Different from the existing methods, our proposed framework not only alleviate bias introduced to the prediction of each individual data, but also provides an approach to understanding how bias arises with the help of two explainers. This is critical for safe GNN deployment in realistic decision-making scenarios.

Federated Graph Machine Learning. Efforts have been made to design federated systems for graph data learning tasks, where these works can be broadly categorized into two settings, Federated Learning with Structured Data and Structured Federated Learning[9]. In the first setting, devices/silos possess graph data and jointly train a graph model orchestrated by a central server. To explore the high-order interactions of user-item graphs while tackling privacy leakage, pseudo-interacted item sampling is proposed [37]. Then CGFL[38] is proposed to dynamically find clusters of clients based on the gradients of GNNs. Additionally, generative models are utilized to deal with the data missing problem [39, 2]. For example, spectral normalized generative adversarial networks (SN-GAN) [39] are proven effective in predicting missing edges and nodes. The second setting of Structured Federated Learning assumes relations exist among clients, where either model parameters[40] or embeddings[41] from each client are transmitted to a central server. Compared with the existing methods, in addition to achieving promising performance under a federated learning scenario, our proposed framework utilizes a sensitive metric to measure the bias introduced by federated learning systems and generative models. Moreover, we provide a potential methodology to facilitate the development of a fairer FGML system in decision-critical cases.

7 Conclusion

In a nutshell, we propose a framework called **EGRASS** to utilize a Generator Module in a distributed subgraph system. The Debias Module is then used to alleviate the node-level bias introduced by a generative model and the federated system. Experimental results evidence the necessity of our proposed framework and point out some future directions we can pursue.

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