Reassessing Fairness: A Reproducibility Study of NIFA's Impact on GNN Models

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Abstract

Graph Neural Networks (GNNs) have demonstrated exceptional performance in processing graph-structured data, yet fairness concerns remain a critical challenge due to GNNs amplifying bias and prejudice in training data. The Node Injection-based Fairness Attack (NIFA) (Luo et al., 2024) was recently proposed as a gray-box method to compromise fairness while maintaining model utility. This study aims to reproduce and validate the claims of NIFA, assessing its impact across multiple datasets and GNN architectures. This reproduction study confirms that NIFA is an effective gray-box attack that degrades the fairness metrics, statistical parity, and equal odds while having a negligible utility loss. Additionally, NIFA's ability to outperform other graph utility and fairness attacks is inconclusive. Finally, we extend the original work by evaluating NIFA's performance under multi-class sensitive attributes and varying levels of homophily. NIFA's ability to degrade fairness shows promising results in a multi-class sensitive attribute environment. Varying levels of homophily showed minimal utility loss and stable fairness metrics across most configurations, with the exception of heterophilic-homophilic and highly homophilic settings. The codebase used in this study can be found at https://anonymous.4open.science/r/Reassessing-NIFA-B4F5/.

1 Introduction

Graph Neural Networks (GNNs) (Gori et al., 2005) excel in learning from graph-structured data with applications in areas like computer vision and recommender systems (Wu et al., 2020). However, fairness remains a critical challenge, as these models often amplify biases in training data, leading to potential societal harms and limiting their use in sensitive domains like recruitment, credit scoring, law enforcement, and healthcare, where biased predictions can reinforce existing inequalities and result in unfair treatment (Dai & Wang, 2021). Existing fairness attacks on GNNs (Hussain et al., 2022; Kang et al., 2023; Zhang et al., 2024b) often rely on modifying connectivity between existing nodes, which is impractical in real-world scenarios due to security restrictions (Luo et al., 2024). To address this, Luo et al. (2024) proposed the Node Injection-based Fairness Attack (NIFA), a more realistic gray-box method that injects synthetic nodes to disrupt fairness while preserving utility metrics like accuracy.

In this work, we aim to critically evaluate the main claims of Luo et al. (2024) by reproducing their results across datasets and GNN architectures, extending their work to support multi-class sensitive attributes and analyzing the role of homophily in NIFA. Our evaluation finds that two of the main claims are partially reproducible: results for attacks on classical GNN models align with the original findings, but two of the three fairness-aware GNN models exhibit discrepancies. The validity of the third claim remains inconclusive due to significant differences between the original and reproduced results. A detailed discussion of these claims follows in the next section.

Beyond reproduction, we conducted additional experiments to generalize NIFA to multi-class sensitive attributes, demonstrating that the attack remains effective. We also analyzed the effect of homophily in graph structured data and found that NIFA's attack strength may correlate with homophily levels; high homophily settings and heterophilic-homophilic ampl amplifies fairness disparities, while lower homophily reduces attack effectiveness.

2 Scope of reproducibility

The objective of this study is to reproduce and validate the key findings presented in the original paper, *Are Your Models Still Fair? Fairness Attacks on Graph Neural Networks via Node Injections*, by Luo et al. (2024). The authors introduce NIFA, a gray-box poisoning attack designed to compromise the fairness of Graph Neural Networks (GNNs) while maintaining minimal impact on their utility. In this reproducibility study, we aim to confirm the following claims and explore their implications:

- **Claim 1**: NIFA can significantly degrade fairness in GNNs, measured by increased Δ_{SP} (Statistical Parity) and Δ_{EO} (Equal Opportunity), while maintaining negligible utility loss across diverse datasets and models, including fairness aware GNNs.
- **Claim 2**: NIFA achieves state-of-the-art performance with a perturbation rate as low as 1%, ensuring scalability and minimal detectability.
- **Claim 3**: Extensive experiments confirm that NIFA outperforms existing fairness and utility attack baselines across multiple datasets.

We replicate the experiments to validate the claims of the original paper, and our contributions are as follows:

- **Multi-Class Sensitive Attributes:** We successfully extend NIFA to handle datasets with multi-class sensitive attributes, reflecting more complex real-world scenarios. This will enable an evaluation of whether the attack can remain effective and scalable in settings with higher attribute diversity.
- **Impact of Homophily on NIFA:** We explore how varying homophily levels in graph structures affect NIFA's effectiveness and fairness, focusing on the interplay between homophily and bias propagation due to node injection. We aim to determine if certain structural properties make networks more susceptible to fairness degradation.

3 Methodology

3.1 Problem Formulation

We adopt notation conventions from Luo et al. (2024). A graph $\mathcal{G} = (\mathcal{V}, \boldsymbol{A}, \boldsymbol{X})$ consists of nodes $\mathcal{V}$, an adjacency matrix $\boldsymbol{A} \in \mathbb{R}^{|\mathcal{V}|\times|\mathcal{V}|}$, and a feature matrix $\boldsymbol{X} \in \mathbb{R}^{|\mathcal{V}|\times D}$. Each node $v \in \mathcal{V}$ has a label $y_v \in \mathcal{Y}$ and a sensitive attribute s. While prior studies limit s to binary values, we generalize s to a k-class setting ($s \in 0, 1, ..., k-1$), where k denotes the number of classes in a sensitive attribute. A GNN-based function f_θ with parameters θ is trained to predict labels using graph signals.

Fairness-related Concepts. In alignment with prior works (Dai & Wang, 2021; Dong et al., 2022; Ling et al., 2023), the authors focus on group fairness. Here, fairness is assessed across groups defined by sensitive attributes. The sensitive attribute divides the node set $\mathcal{V}$ into two disjoint groups: $\mathcal{V}_0$, where $s = 0$, and $\mathcal{V}_1$, where $s = 1$. Group fairness is assessed using two primary metrics: Statistical Parity (SP) and Equal Opportunity (EO). These metrics evaluate the independence of predictions and correct predictions, respectively, from the sensitive attribute.

SP. Statistical Parity requires that the model's predictions are independent of the sensitive attribute. Formally, for any predicted class $y \in \mathcal{Y}$, the following condition should hold:

$$P(\hat{y}_v = y|s = 0) = P(\hat{y}_v = y|s = 1) \tag{1}$$

where $\hat{y}_v$ denotes the predicted label for node v. Statistical Parity ensures that the distribution of predictions is uniform across sensitive groups, regardless of their occurrence in the graph.

EO. Equal Opportunity focuses on the model's ability to predict the correct label independently of the sensitive attribute. For any true class $y \in \mathcal{Y}$, it requires that:

$$P(\hat{y}_v = y | y_v = y, s = 0) = P(\hat{y}_v = y | y_v = y, s = 1) \tag{2}$$

Where y_v represents the true label of node v. Equal Opportunity ensures that the likelihood of correct predictions is consistent across sensitive groups.

The degree to which fairness is violated is quantified using two metrics, Δ_{SP} and Δ_{EO}, which measure deviations from the ideal conditions described above. These metrics are defined as follows:

$$\Delta_{SP} = \mathbb{E}[P(\hat{y} = y | s = 0) - P(\hat{y} = y | s = 1)] \tag{3}$$

$$\Delta_{EO} = \mathbb{E}[P(\hat{y} = y | \hat{y}_v, s = 0) - P(\hat{y} = y | \hat{y}_v, s = 1)] \tag{4}$$

For both metrics, smaller values indicate better fairness, with $\Delta_{SP} = 0$ and $\Delta_{EO} = 0$ representing perfect fairness.

Attack Definition. Following the line of previous attacks on GNNs (Sun et al., 2020; Zhang et al., 2024a), the authors launch a fairness-targeted attack on GNN models through the application of node injection during the training phase. Operating under a gray-box setting, the attacker has access to the graph structure $\mathcal{G}$, node labels $\mathcal{Y}$, and sensitive attributes s. However, the attacker lacks knowledge of the model architecture or parameters.

The attack involves injecting malicious nodes $\mathcal{V}_I$ into the graph during training to degrade fairness while maintaining model accuracy. The modified graph $\mathcal{G}' = (\mathcal{V}', \boldsymbol{A}', \boldsymbol{X}')$ includes injected nodes with trained features and connections. The goal is to maximize Δ_{SP} and Δ_{EO} under constraints on the number of injected nodes ($|\mathcal{V}_I| \leq b$) and their connectivity ($deg(v) \leq d$). The objective is expressed as:

$$\max_{\mathcal{G}'} \left|\mathcal{F}(f_{\theta^*}(\mathcal{V}, \mathcal{G}'))\right| \quad \text{s.t.} \quad \arg\max_{\theta^*} \mathcal{M}(f_{\theta^*}(\mathcal{V}, \mathcal{G}')), \quad |\mathcal{V}_I| \leq b, \quad deg(v)_{v \in \mathcal{V}_I} \leq d \tag{5}$$

where $\mathcal{F}(\cdot)$ and $\mathcal{M}(\cdot)$ are evaluation functions for fairness and utility, respectively. Constraints on the number of injected nodes ($|\mathcal{V}_I| \leq b$) and their connectivity ($deg(v)_{v \in \mathcal{V}_I} \leq d$) ensure that the attack remains unnoticeable and deceptive to the defenders, both b and d are predefined budgets.

3.2 Model framework

The NIFA framework combines node injection and feature optimization to degrade fairness in GNNs. It follows two principles for node injection: (1) Uncertainty-maximization, which uses a Bayesian GNN (Liu et al., 2022) to target nodes with high uncertainty near decision boundaries, and (2) Homophily-increase, which ensures injected nodes connect exclusively to nodes within the same sensitive group, amplifying intra-group information propagation and increasing the homophily ratio.

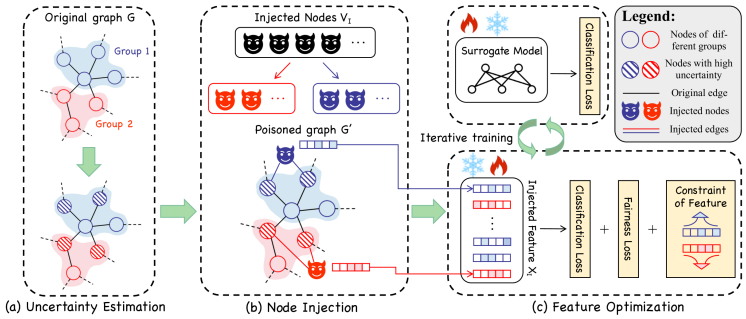

Figure 1: Overview of the NIFA framework (Luo et al., 2024)

Injected nodes' features are optimized using multiple objectives to balance fairness degradation and utility preservation. An iterative strategy prevents overfitting to surrogate model parameters. The framework's components—uncertainty maximization, node injection, and feature optimization—are visualized in Figure 1 and detailed below.

Uncertainty-maximization. Nodes with high uncertainty are selected for injection as their predictions are more vulnerable to adversarial attacks. A Bayesian GNN with Monte Carlo (MC) dropout approximates parameter distributions (Liu et al., 2022), introducing variability in predictions through sampled dropout masks. Uncertainty scores are computed as the variance of predictions across samples:

$$U = \mathrm{Var}_{i=1}^{T}\big(f_{\theta_{B_i}}(\mathcal{V}, \mathcal{G})\big). \tag{6}$$

where T is the number of samples and $f_{\theta_{B_i}}(\cdot)$ is the mapping function with the i-th sampled Bayesian GNN parameters θ_{B_i}. Nodes with the top $k\%$ uncertainty within each sensitive group are selected, with k as a tunable hyperparameter.

Homophily-increase. Injected nodes are distributed among sensitive groups and connect to d random target nodes within the same group, where d is a hyperparameter (Figure 1b). This strategy prevents intra-group information propagation, exacerbating unfairness by increasing node-level homophily:

$$\mathcal{H}_u = \frac{\sum_{v \in \mathcal{N}_u} \mathbb{1}(s_u = s_v)}{|\mathcal{N}_u|}, \tag{7}$$

where $\mathcal{N}_u$ represents the neighbors of node u, s_u is the sensitive attribute of u, and $\mathbb{1}(\cdot)$ is the indicator function.

Feature optimization. Injected nodes' features $\mathbf{X}_i$ are optimized to enhance the effectiveness of NIFA. In a gray-box attack setting, attackers lack direct visibility of victim models and instead train a surrogate GNN model $\mathcal{S}$ on the poisoned graph $\mathcal{G}'$. The surrogate model $\mathcal{S}$ is trained iteratively alongside $\mathbf{X}_i$ using different objectives, preventing overfitting to specific model parameters. While $\mathcal{S}$ follows a standard GNN training process with cross-entropy loss, the optimization of $\mathbf{X}_i$ incorporates multiple objective functions to maximize unfairness while maintaining utility. Specifically, the optimization framework balances three key components: (1) classification loss to preserve predictive performance, (2) fairness loss to amplify disparities, and (3) a feature constraint to reinforce information differences across sensitive groups. The details of these loss functions and their implementation are presented in Appendix A.

3.3 Additional Experiments

The previous sections have outlined the foundational work presented in (Luo et al., 2024). In this section, we provide a detailed explanation of the contributions of this study.

Multi-class sensitive attributes. In real-world scenarios, sensitive attributes often tend to be non-binary (Duong & Conrad, 2023). To adapt the NIFA attack to these complex scenarios, the attack is generalized to operate on multi-class sensitive attributes. This extension involves two main components. Firstly, the fairness metrics must be generalized to accommodate multiple sensitive attribute classes. Secondly, the attack methodology requires adaptation to effectively address multiple sensitive groups.

To maintain consistency with the binary-sensitive attribute metrics established in the original paper, the One-vs-All (OvA) and One-vs-One (OvO) approaches are explored. These methods, commonly used in multi-class classification, allow multi-class problems to be approached by aggregating the results of binary classifiers. In the same way, these techniques can be used to generalize the binary metrics to multi-class sensitive attributes by aggregating binary metrics. Comparable approaches have been utilized in prior research, where the One-vs-All method has been successfully applied to extend fairness metrics (Rouzot et al., 2022; Krasanakis et al., 2018).

In the One-vs-All approach, the binary metrics, as introduced in Equations (1–2), are computed for each sensitive group against the remainder of the nodes. These binary results are then aggregated into a single metric by computing the expected value over all sensitive groups $a \in \mathcal{A}$ and all labels $y \in \mathcal{Y}$:

$$\Delta_{SP\text{-}OvA} = \mathbb{E}[|P(\hat{y} = y|s = a) - P(\hat{y} = y|s \neq a)|] \tag{8}$$

$$\Delta_{EO\text{-}OvA} = \mathbb{E}[|P(\hat{y} = y|y_v = y, s = a) - P(\hat{y} = y|y_v = y, s \neq a)|] \tag{9}$$

In contrast, the One-vs-One approach computes the expected value for the results of the binary metrics, which are computed for all possible combinations of the sensitive groups $(a_1, a_2) \in \{(x, y)|x, y \in \mathcal{A}, x \neq y, x < y\}$ for all labels $y \in \mathcal{Y}$:

$$\Delta_{SP\text{-}OvO} = \mathbb{E}[|P(\hat{y} = y|s = a_1) - P(\hat{y} = y|s = a_2)|] \tag{10}$$

$$\Delta_{EO\text{-}OvO} = \mathbb{E}[|P(\hat{y} = y|y_v = y, s = a_1) - P(\hat{y} = y|y_v = y, s = a_2)|] \tag{11}$$

Two modifications to the model framework are applied to ensure the attack methodology works. First, the node injection process must be adjusted to ensure an equal proportion of injected nodes connect to each sensitive group while maintaining the homophily-increase principle. Second, the most significant change lies in feature optimization, where generalized metrics must be transformed into corresponding loss functions. The existing loss functions, detailed in Appendix A, are extended in line with the generalization of metrics. For the One-vs-All approach, L_{SP} and L_{EO} are computed for each sensitive group versus the remaining groups, and the mean of these losses is used for optimization. Whereas in the One-vs-One approach, the mean losses are calculated across all pairwise combinations of sensitive attributes. The resulting mean losses will replace the L_{SP} and L_{EO} in the optimization objective.

Homophily Evaluation. To investigate the relationship between homophily and the effectiveness of NIFA, we adopt a systematic methodology involving graph generation, GNN training, and fairness analysis. Graph structures with varying homophily levels are constructed using a synthetic dataset. For these graphs, the Directed Preferential Attachment with Homophily (DPAH) model (Espín-Noboa et al., 2022) is employed to precisely control homophily parameters, enabling exploration across a spectrum of heterophilic to homophilic configurations. To ensure a fair comparison, we also calculate the overall homophily rates for both the synthetic and original datasets. These configurations are shown in Figure 2. Beyond these predefined graphs, we explore a wide range of homophily rate combinations, detailed in Appendix D, building on insights from Ferrara et al. (2022).

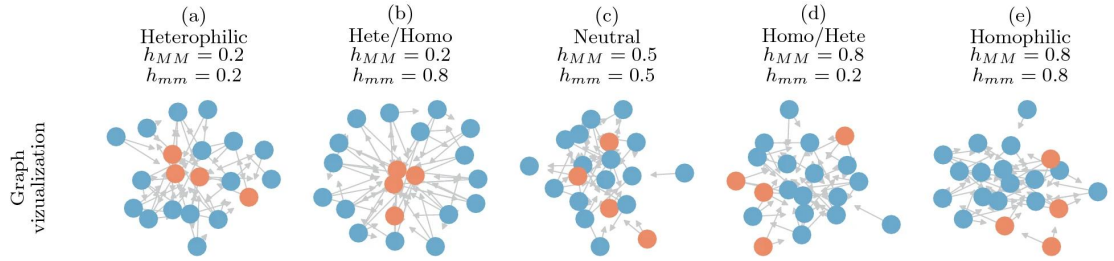

Figure 2: Graph examples of different levels of homophily (Espín-Noboa et al., 2022)

The standard GCN model used in Luo et al. (2024) is used to train generated graphs under consistent experimental conditions. Similarly to the original paper, performance is evaluated on their ability to predict node labels. The NIFA framework is then applied across all homophily scenarios, with node injections optimized to target fairness. The perturbation rate is maintained at 1% to ensure minimal detectability, as per the original study. The impact of the attack is assessed by measuring changes in fairness metrics (Δ_{SP} and Δ_{EO}) and utility preservation.

Fairness impact is further analyzed by examining how varying homophily levels influence NIFA's ability to isolate minority nodes and exacerbate fairness disparities. The attack's effectiveness is quantified by evaluating the degradation in both fairness and model utility, with attention to the role of structural graph properties in mediating these effects. Through this comprehensive framework, we aim to provide insights into the interplay between homophily and fairness vulnerabilities, as well as strategies for mitigating adversarial attacks in graph-based models.

4 Experimental Setup and Code

The code to run NIFA on the four classic GNN models, including datasets and package requirements, is publicly available on the authors' official code repository[1]. This code runs without requiring major modifications, although installing the correct packages was necessary as some library-specific updates have been made since. Code for reproducing the other experiments, such as running fairness-aware models and performing utility and fairness attacks, was not provided. To perform these experiments, their respective code repositories were independently accessed and made compatible with the NIFA-generated graphs. An updated list of requirements was created to ensure compatibility with our hardware, which is also included in the code repository. All reproduction experiments are run five times, as done in the original paper.

4.1 Datasets

Original Datasets. The experiments conducted in the original paper utilized three different real-world datasets: **Pokec-z**, **Pokec-n**[2], and **DBLP**[3]. Pokec-z and Pokec-n are subsets of the Pokec network. According to Takac & Zabovsky (2012), Pokec is the most popular social network in Slovakia and is also widely used in the Czech Republic. In this dataset, nodes represent users, while edges represent unidirectional following relationships (Luo et al., 2024).

The DBLP dataset is a citation dataset containing a digital library of comprehensive coverage of database literature (Elmacioglu & Lee, 2005). Each node represents an author, and two authors are connected if they have co-authored at least one paper. The node features are derived from words extracted from the published papers of the corresponding author (Luo et al., 2024). The specifics of each dataset, as well as their respective homophily rates, are summarized in Table 4 in Appendix C. Pokec-z and Pokec-n contain significantly larger numbers of nodes and edges than DBLP, while DBLP has the highest feature dimensionality.

Multi-class Sensitive Attribute Dataset. To the best of our knowledge, there are no graph datasets for node classification with explicit multi-class sensitive attributes. To accommodate for this, the method proposed by Purificato et al. (2024) is adopted, which involves augmenting a dataset that has binary sensitive attributes to produce multi-class sensitive attributes. This augmentation is achieved by converting other potentially sensitive features into classes, for example, through binning. We follow the approach introduced by Purificato et al. (2024), who applied this technique to the Pokec dataset by creating a new sensitive attribute. Specifically, the age feature was binned into the following ranges to form five age groups: 0-17, 18-23, 24-28, 29-35, and 36 and above. These experiments aim to compare the OvA and OvO approaches to generalizing the NIFA attack to multi-class sensitive attributes.

Synthetic Dataset. To investigate the impact of homophily rates, we construct a synthetic dataset based on the work by Espín-Noboa et al. (2022). The dataset consists of synthetic networks generated using the Directed Preferential Attachment with Homophily (DPAH) model[4], which integrates both preferential attachment and homophily. Further details on the model's structure are provided in Appendix D.

The dataset lacks explicit node features and only includes binary labels for majority and minority groups. To adapt this dataset for use within the NIFA pipeline, we generate proxy features by introducing a synthetic node classification task. We first assign proxy class labels to the nodes based on two Gaussian distributions. For a given node i, its proxy class label y_i is determined by sampling from two Gaussian distributions $\mathcal{N}(\mu_1, \sigma^2)$ and $\mathcal{N}(\mu_2, \sigma^2)$, where the mean vectors μ_1 and μ_2 represent the centers of the proxy classes, and σ^2 controls the variance within each class. These proxy labels serve as a basis for creating features required for the NIFA pipeline.

[1]https://github.com/CGCL-codes/NIFA
[2]https://snap.stanford.edu/data/soc-pokec.html
[3]DBLP. Computer Science Bibliography
[4]https://github.com/gesiscss/Homophilic_Directed_ScaleFree_Networks

To construct the feature space, a n-dimensional feature vector $\mathbf{x}_i \in \mathbb{R}^n$ was generated for each node i, where each feature dimension is sampled from the Gaussian corresponding to its assigned proxy label. Specifically:

$$\mathbf{x}_i \sim \begin{cases} \mathcal{N}(\mu_1, \sigma^2), & \text{if } y_i = 0, \\ \mathcal{N}(\mu_2, \sigma^2), & \text{if } y_i = 1. \end{cases}$$

A correlation parameter ρ is introduced to establish a statistical relationship between the Gaussian distributions and the proxy labels. This ensures that the feature space effectively reflects the proxy labels, making the nodes distinguishable and enabling the creation of a meaningful node classification task. The sensitive attribute $s_i \in \{0, 1\}$, indicating whether a node belongs to the majority ($s_i = 0$) or minority ($s_i = 1$) group, remains binary. We divide the dataset into train (70%), validation (15%), and test (15%) splits. Each split preserves the original distribution of sensitive attributes and proxy labels to minimize sampling bias.

4.2 Model descriptions

Classical GNN Models. To reproduce the original NIFA results on classical models, GCN (Kipf & Welling, 2017), GraphSAGE (Hamilton et al., 2017), APPNP (Gasteiger et al., 2022), and SGC (Wu et al., 2019), the code provided on the GitHub repository was used without significant modifications. Further clarifications on these models are found in Appendix B.1.

Fairness Aware Models. Reproducing the results of the fairness aware models, specifically FairGNN (Dai & Wang, 2021), FairVGNN (Wang et al., 2022), and FairSIN (Ju et al., 2023) (see Appendix B.1 for more details), proved to be more complex than reproducing those of the classical models. Adjustments to the code of the fairness-aware models were necessary to ensure valid results. Specifically, NIFA's poisoned graphs needed to be stored for each dataset and loaded through a custom data loading function to maintain compatibility with the fairness model pipelines. Additionally, minor modifications to the training logic, including adjustments to the loss functions, were required. Finally, the exact fairness metrics outlined in subsection 3.1 had to be implemented within each fairness model.

Baseline Attack Models. The authors of the original paper compared NIFA to various competitors, including attacks based on utility: AFGSM (Wang et al., 2020), TDGIA (Zou et al., 2021), G^2A2C (Ju et al., 2023), and attacks based on fairness: FA-GNN (Hussain et al., 2022), FATE (Kang et al., 2023), G-FairAttack (Zhang et al., 2024b). Due to time limitations and the need to reproduce these models independently, two of these models were reproduced: the utility-based attack TDGIA and the fairness-based attack FA-GNN. Their details are found in Appendix B.2.

To reproduce the FA-GNN results, two minor modifications were made to the code: the graph-loading process was adjusted, and the fairness metrics detailed in subsection 3.1 were implemented. To obtain results for TDGIA, the graphs were poisoned by TDGIA and evaluated on the NIFA fairness metrics. Three modifications were made to the codebase: the TDGIA graph-handling method was adjusted, a graph transformation step was implemented in the NIFA code, and parts of the NIFA implementation were disabled to prevent already poisoned graphs from being reattacked.

4.3 Computational requirements

All our experiments were conducted utilizing NVIDIA A100 GPUs with CUDA 12.1.1. We tried to closely replicate the Python environment specified by the authors to ensure consistency. Specifically, we used Python 3.10.16 and PyTorch 2.4.0. For the Deep Graph Library (DGL), we employed version 2.4.0, which requires PyTorch $\leq$ 2.4.0, a constraint we adhered to for compatibility. Additionally, we incorporated the PyTorch Geometric (PyG) library version 2.6.1, along with auxiliary libraries like torch- scatter and torch-sparse, all compatible with CUDA 12.1.1.

5 Results

5.1 Results reproducing the original paper

The reproduced outcomes of the models described in subsection 4.2 are presented in Table 1. The reproduced results for utility- and fairness-based attacks are presented in Table 2. In alignment with the original work, we report the mean and standard deviation for all results in this section. The results from the original paper are provided in Appendix E.

Table 1: Attack performance of NIFA on different victim GNN models. Results are reported in percentages (%). To showcase trends similar to the original paper, we **bold** the results where NIFA successfully degraded the fairness of victim GNN models.

		Pokec-z			**Pokec-n**			**DBLP**		
		Accuracy	Δ_{SP}	Δ_{EO}	Accuracy	Δ_{SP}	Δ_{EO}	Accuracy	Δ_{SP}	Δ_{EO}
GCN	Before	71.27 ± 0.22	7.74 ± 0.39	5.82 ± 0.34	71.12 ± 0.34	0.74 ± 0.47	2.08 ± 0.84	96.13 ± 0.76	3.74 ± 1.08	2.31 ± 1.32
	After	70.99 ± 0.55	**15.74 ± 1.03**	**13.91 ± 1.07**	70.38 ± 0.48	**7.94 ± 0.71**	**7.89 ± 0.91**	92.96 ± 1.64	**11.12 ± 4.37**	**18.43 ± 4.10**
GraphSAGE	Before	70.58 ± 0.76	5.01 ± 1.48	3.50 ± 0.77	68.77 ± 0.34	1.65 ± 1.31	2.34 ± 1.04	96.03± 0.37	4.65 ± 2.81	4.40 ± 0.65
	After	69.62 ± 0.56	**5.81 ± 1.19**	**4.08 ± 0.89**	68.93 ± 1.19	**3.32 ± 1.88**	**3.56 ± 1.91**	94.42 ± 0.92	**8.08± 1.24**	**14.08 ± 1.90**
APPNP	Before	69.28 ± 0.83	7.05 ± 0.50	5.29 ± 0.49	68.573 ± 0.37	5.02 ± 0.75	5.34 ± 0.74	96.53 ± 0.33	4.39 ± 0.88	2.94 ± 1.21
	After	69.46 ± 0.43	**18.88 ± 1.29**	**17.42 ± 1.33**	68.32 ± 0.46	**7.74 ± 2.61**	**7.40 ± 2.58**	92.26 ± 1.05	**12.61 ± 4.88**	**18.94 ± 6.33**
SGC	Before	66.65 ± 3.42	6.63 ± 1.63	5.38 ± 0.95	66.42 ± 3.25	4.18 ± 2.23	4.69 ± 1.93	96.58 ± 0.47	4.07 ± 0.47	2.67 ± 0.68
	After	67.02 ± 1.56	**14.53 ± 2.75**	**12.99 ± 2.74**	67.43 ± 0.69	**9.93± 3.00**	**9.58 ± 2.96**	92.81 ± 0.76	**10.21 ± 5.55**	**16.44 ± 7.05**
FairGNN	Before	72.10 ± 0.12	5.12 ± 0.58	3.04 ± 0.63	70.87 ± 0.21	0.91 ± 0.61	1.39 ± 0.46	95.38 ± 0.41	3.27 ± 2.28	3.79 ± 1.16
	After	70.98 ± 0.14	**5.30 ± 0.64**	**3.17 ± 0.67**	71.07 ± 0.28	**2.02 ± 1.42**	**2.86 ± 0.90**	95.53 ± 0.29	**4.46 ± 1.53**	**8.54 ± 2.12**
FairVGNN	Before	66.65 ± 0.91	1.35 ± 0.39	3.48 ± 0.51	64.75 ± 2.81	1.26 ± 0.66	1.31 ± 0.70	95.58 ± 0.47	3.97 ± 0.98	1.91 ± 0.68
	After	66.43 ± 0.95	**1.95 ± 1.16**	**3.69 ± 1.26**	65.67 ± 2.84	**2.89 ± 2.12**	**3.55 ± 1.32**	90.25 ± 1.12	**11.13 ± 5.75**	**17.70 ± 7.91**
FairSIN	Before	68.3 ± 0.35	3.79 ± 1.85	3.96 ± 1.67	61.34 ± 3.82	3.33 ± 1.67	5.00 ± 1.87	94.32 ± 0.67	1.22 ± 0.78	3.40 ± 1.48
	After	64.14 ± 5.66	**4.33 ± 2.81**	3.65 ± 2.58	64.51 ± 2.7	1.80 ± 0.95	4.14 ± 1.11	90.50 ± 1.40	**13.47 ± 3.09**	**37.31 ± 5.74**

The original paper highlights two key claims regarding NIFA's performance. The authors support these claims by demonstrating substantial increases in Δ_{SP} and Δ_{EO} across all classical GNN models. For instance, on the Pokec-z dataset, Δ_{SP} and Δ_{EO} of GCN increased significantly from 7.13% and 5.10% to 17.36% and 15.59%, respectively. Even on fairness-aware models, NIFA showed a significant impact, with the Δ_{EO} of FairVGNN on Pokec-z rising from 2.59% to 9.28%, a nearly fourfold increase in fairness degradation. Furthermore, the attack does not sacrifice the utility of the GNN models, as the utility of nearly all models only decreases a few percentage points after the attack. However, our application of NIFA across various models found that the original results were only partially reproducible.

The reproduced attack results of the classical GNN models mostly align with the original findings. Although our Δ_{SP} and Δ_{EO} values are generally slightly lower, this trend holds for both pre-attack and post-attack results. Importantly, the ratio between the pre- and post-attack metrics remains consistent. For instance, on the Pokec-z dataset, all classical models exhibit an approximate twofold increase in Δ_{SP} and Δ_{EO} after the attack, matching the pattern reported in the original paper. Similar ratios were also observed across the other two datasets.

The reproduced results of the attack on the fairness-aware models show less similarity to the original findings. In the original study, the attacks on the Pokec-z and Pokec-n datasets show Δ_{SP} and Δ_{EO} differences, ranging from double to twentyfold increases. Whereas our reproduced results on both Pokec datasets only show minor increases, with fairness metrics even decreasing in three cases. Based on this analysis we conclude that the first and second claims hold completely for the attacks on the classical models. However, for fairness-aware models, these claims only partially hold, as the reproduced results diverge from the original findings in two of the three datasets.

The third and final claim made by the authors is that NIFA outperforms existing fairness and utility attack baselines across multiple datasets. This claim is supported by comparisons with six established graph attacks, evenly split between utility and fairness attacks. To evaluate this claim, we reproduced one attack from each category. In the original paper, NIFA outperforms both TDGIA and FA-GNN in terms of Δ_{SP} and Δ_{EO} metrics. For example, on the Pokec-n dataset, TDGIA and FA-GNN have a Δ_{SP} score of 5.35% and 2.64% respectively. In contrast, NIFA has a Δ_{SP} score of 10.10%, which is a significant increase. After reproducing

Table 2: Accuracy and Fairness performance of attack launched by the different attackers. The results are reported in percentages (%).

	Pokec-z			Pokec-n			DBLP		
	Accuracy	Δ_{SP}	Δ_{EO}	Accuracy	Δ_{SP}	Δ_{EO}	Accuracy	Δ_{SP}	Δ_{EO}
Clean	71.27 ± 0.22	7.74 ± 0.39	5.82 ± 0.34	71.12 ± 0.34	0.74 ± 0.47	2.08 ± 0.84	95.88 ± 1.61	3.84 ± 0.34	1.91 ± 0.75
Utility attacks on GNNs									
TDGIA	66.56 ± 2.65	9.60 ± 1.47	7.92 ± 1.59	67.09 ± 1.94	0.64 ± 0.37	1.31 ± 0.29	90.90 ± 0.58	5.97 ± 0.76	3.61 ± 0.64
Fairness attacks on GNNs									
FA-GNN	71.07 ± 0.76	5.89 ± 2.23	4.41 ± 1.98	71.11 ± 0.51	3.21 ± 0.62	2.57 ± 1.61	95.39 ± 0.90	1.63 ± 1.20	3.15 ± 1.48
NIFA	70.99 ± 0.55	**15.74 ± 1.03**	**13.91 ± 1.07**	70.38 ± 0.48	**7.94 ± 0.71**	**7.89 ± 0.91**	92.96 ± 1.64	**11.12 ± 4.37**	**18.43 ± 4.10**

the results of the different attack baselines, increases in fairness metrics are found for all datasets compared to NIFA as well. However, the absolute values of these attacks are not in accordance with the original findings. Even though the general trend of NIFA having a bigger impact on the metrics than the baseline models is true, we can not conclusively say that claim 3 holds due to the large discrepancies between the original and reproduced results.

5.2 Results beyond the original paper

We conducted two additional experiments to evaluate NIFA's attack on fairness: one extending the sensitive attribute to a multi-class setting and another analyzing its effects across different graph structures.

Multi-class sensitive attributes. The experimental results of NIFA on the augmented Pokec datasets with multi-class sensitive attributes described in section 4.1 are presented in Table 3. These results include both the OvA and OvO approaches, where the mean and standard deviation across five random seeds are reported. Note that the fairness metrics correspond to the respective OvA and OvO versions.

Table 3: NIFA attack performance on augmented Pokec-z and Pokec-n datasets using GCN. Results are in percentages (%) with the best fairness metrics in **bold**.

	Pokec-z			Pokec-n		
	Accuracy	Δ_{SP}	Δ_{EO}	Accuracy	Δ_{SP}	Δ_{EO}
OvA						
Before	71.11 ± 0.14	39.19 ± 0.38	25.58 ± 0.32	70.64 ± 0.22	40.81 ± 1.08	26.51 ± 3.12
After	70.88 ± 0.63	**42.84 ± 0.46**	**38.89 ± 0.76**	71.12 ± 0.70	**46.25 ± 0.82**	**34.52 ± 1.37**
OvO						
Before	71.31 ± 0.17	37.74 ± 0.39	31.03 ± 0.37	70.67 ± 0.17	40.17 ± 0.85	26.05 ± 2.86
After	71.29 ± 0.49	**39.88 ± 0.32**	**39.88 ± 1.15**	70.67 ± 0.43	**43.98 ± 0.33**	**33.36 ± 0.34**

The results of NIFA utilizing multi-class sensitive attributes indicate that the authors' claims remain valid in this setting. As observed in Table 3, the model's utility remains comparable to that of the model trained on the clean graph. Simultaneously, the fairness scores demonstrate that the attack was effective, further supporting the authors' claims. However, the absolute values are higher compared to the original results, which we attribute to the use of a different sensitive attribute that changes the feature set of the nodes.

Synthetic dataset. The impact of the NIFA attack on fairness across various synthetic graph structures and their homophily values, as described in section 3.3, is shown in Figure 3. Results are reported as the mean and standard deviation across five random seeds. A minority fraction of $f_m = 0.3$ is shown as this most closely resembles minority fractions of the original datasets, found in subsection 4.1, Appendix C.

Exploratory analysis, conducted on the predefined graph structures in Figure 2, showed minimal utility loss, consistent with previous findings for NIFA. Interestingly, the Δ_{SP} and Δ_{EO} fairness metrics remained stable across most configurations, with the exception of heterophilic-homophilic and highly homophilic settings. Indicating that these two settings may have more impact on the fairness degradation of NIFA. For highly

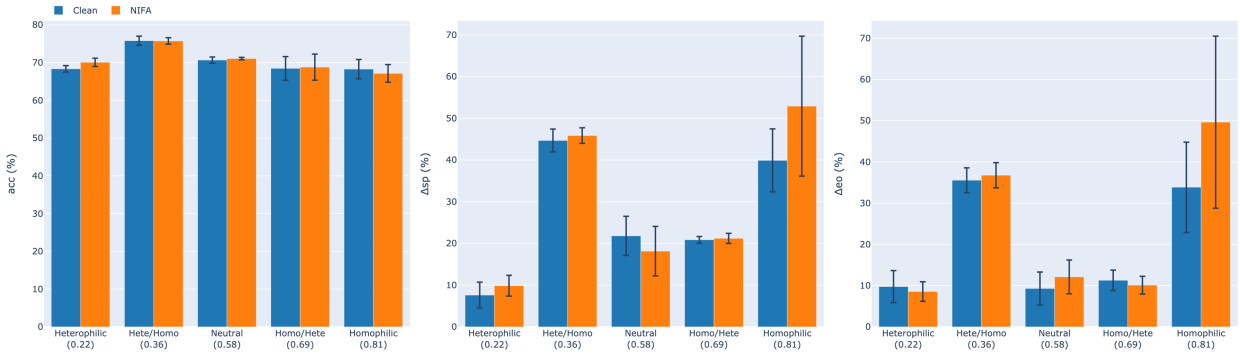

Figure 3: Effect of edge homophily on fairness metrics before and after the NIFA attack ($f_m = 0.3$).

homophilic settings, a large variance is observed over the different runs. This suggests that denser graphs may exhibit more random behavior when attacked by NIFA.

6 Discussion

6.1 Discussion of the results

The primary goal of this study was to reproduce and validate the three main claims made by the original paper *Are Your Models Still Fair? Fairness Attacks on Graph Neural Networks via Node Injections* by Luo et al. (2024). As shown in subsection 5.1, claim 1 and 2 partially hold, whereas claim 3 is inconclusive. Several factors may have contributed to differences in the results. First, only the classical GNN victim models were available on the official NIFA code repository. As a result, the fairness-aware models and baseline attack models had to be independently sourced and implemented, potentially leading to design choices that differed from those of the original authors. We adhered to the original code implementations of these models unless otherwise specified in the referenced papers. This likely explains the significant discrepancies between the models' original and reproduced results. Second, due to randomness and an unknown seed, replicating the exact outcomes reported in the original paper was not possible.

The proposed multi-class sensitive attribute implementation demonstrates similar fairness degradation trends to binary sensitive attribute datasets. These findings suggest that NIFA remains effective with multi-class sensitive attributes and supports an extension of the fairness metric itself.

Furthermore, our results on homophily influence on NIFA reveal significant differences between datasets with heterophilic-homophilic and fully homophilic structures. Given that the datasets in the original NIFA experiments also exhibit high homophily, this might suggest that NIFA's pronounced impact on those graphs may be partially driven by their homophilic nature, raising concerns about its effectiveness on graphs with lower homophily. These findings offer initial insights into the role of homophily in fairness attacks on GNNs. However, datasets with high homophily demonstrated greater variability across different seeds, indicating the need for caution when interpreting results. While the relationship between homophily and fairness deserves further investigation, definitive conclusions cannot be drawn at this stage. A more comprehensive exploration is left for future work.

6.2 Reflection: What was easy? What was difficult?

After resolving dependency issues, the reproduction of the attack performance of NIFA on the classical GNN models was achieved without problems. The code in the GitHub repository was well-organized, and the README was thoroughly documented for these models.

Due to the lack of support for CUDA versions older than 11.6.0 and the deprecation of some dependencies specified in the NIFA repository, we were unable to fully adhere to the stated requirements. Consequently, parts of the code of repositories of the other models had to be modified, as certain functionalities relied on older versions of DGL.

Certain aspects of the reproduction process were unclear. For example, reproducing the results required using additional code repositories, but the original paper did not specify how these should be integrated. Although NIFA's code was well-structured, the other repositories presented challenges, such as adapting the dataset loading structure for Pokec and DBLP to ensure compatibility and making modifications to specific functions. We provide details on these modifications in subsection 4.2.

6.3 Communication with original authors

We contacted the original authors of the paper twice to seek clarification on aspects of their implementation of the fairness-aware models and baseline attack models. The inquiries focused on understanding implementation details, such as confirming the configuration of key parameters, verifying any updates to the official code repository, and clarifying certain techniques used in experiments that were not fully documented in the paper. Both inquiries received prompt and helpful responses, for which their clarifications and timely assistance are greatly appreciated.

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Appendices

A Feature optimization

The feature optimization background is directly adapted from Luo et al. (2024).

Classification loss. To ensure the utility of the victim model remains unaffected and avoid detection, the authors employ the cross-entropy loss as the first objective function:

$$L_{CE} = -\frac{1}{|\mathcal{V}^{tr}|} \sum_{u \in \mathcal{V}^{tr}} y_u \log h_u \tag{12}$$

where $\mathcal{V}^{tr}$ denotes the original training node set,y_u is the true label of node u, and h_u is the output logits of node u.

Fairness loss. To maximize unfairness, two fairness loss functions are defined based on the metrics Δ_{SP} and Δ_O:

$$L_{SP} = -\| \frac{1}{|\mathcal{V}_0^{tr}|} \sum_{u \in \mathcal{V}_0^{tr}} h_u - \frac{1}{|\mathcal{V}_1^{tr}|} \sum_{u \in \mathcal{V}_1^{tr}} h_u \|_2^2, \tag{13}$$

$$L_{EO} = -\| \sum_{y \in \mathcal{Y}} (\frac{1}{|\mathcal{V}_{0,y}^{tr}|} \sum_{u \in \mathcal{V}_{0,y}^{tr}} h_{u,y} - \frac{1}{|\mathcal{V}_{1,y}^{tr}|} \sum_{u \in \mathcal{V}_{1,y}^{tr}} h_{u,y}) \|_2^2, \tag{14}$$

where $h_u \in \mathbb{R}^{|\mathcal{Y}|}$ represents the raw output for node u, and $h_{u,y}$ is the output for class y. $\mathcal{V}_{i,y}^{tr}$ denotes the set of training nodes with sensitive attribute i and label y.

Constraint of feature. To distinguish information introduced by injected nodes between sensitive groups during message propagation, the authors define a feature constraint:

$$L_{CF} = -\| \frac{1}{|\mathcal{V}_{I,0}|} \sum_{u \in \mathcal{V}_{I,0}} \mathbf{X}_{I,u} - \frac{1}{|\mathcal{V}_{I,1}|} \sum_{u \in \mathcal{V}_{I,1}} \mathbf{X}_{I,u} \|_2^2, \tag{15}$$

where $V_{I,i}$ is the set of injected nodes connected to sensitive group i.

Overall loss. The overall loss for optimizing the injected nodes' features is defined as:

$$L = L_{CE} + \alpha \cdot L_{CF} + \beta \cdot (L_{SP} + L_{EO}), \tag{16}$$

where α and β are hyperparameters controlling the weight of each term.

B Additional model descriptions

B.1 Victim models

GCN (Kipf & Welling, 2017): A GNN is based on convolutions that operate directly on graphs. All local node information is aggregated to generate graph representations, enabling semi-supervised learning on graph-structured data.

GraphSAGE (Hamilton et al., 2017): A framework for inductive node embedding that uses node features to learn an embedding function that is able to generalize unseen nodes. By integrating node features into the learning algorithm, the model captures the topological structure of each node's neighborhood.

APPNP (Gasteiger et al., 2022): This model uses GCN and PageRank to develop a framework called personalized propagation of neural predictions (APPNP), which utilizes a large adjustable neighborhood for classification and can be integrated with any neural network.

SGC (Wu et al., 2019): Motivated by the inherent complexity of GCNs, this model simplifies them by removing non-linearities between layers, reducing the function to a single linear transformation.

FairGNN (Dai & Wang, 2021): This model is designed to mitigate bias in GNNs while preserving high node classification accuracy by utilizing graph structures and minimal sensitive information.

FairVGNN (Wang et al., 2022): Motivated by an observation of sensitive information leakage in GNNs, FairVGNN creates fair node features by automatically detecting and masking sensitive-correlated features, taking the variation of correlations after feature propagation into account.

FairSIN (Yang et al., 2024): Current methods address GNNs bias in predictions due to sensitive attributes by filtering out sensitive information. This has the potential of filtering out non-sensitive feature information, resulting in a trade-off between predictive performance and fairness. To overcome this, FairSIN incorporates Fairness-facilitating Features (F3) into node features or representations prior to message passing, with the goal of statistically neutralizing bias while retaining non-sensitive information.

B.2 Baseline attacks

TDGIA (Zou et al., 2021): An injection attack based on topological vulnerability implements a defective edge strategy to identify the original nodes for connection with injected nodes. It then formulates a smooth feature optimization to generate features for the injected nodes.

FA-GNN (Hussain et al., 2022): This study highlighted the susceptibility of GNN models to adversarial fairness attacks by empirically identifying several edge injection strategies, which could compromise GNN fairness with only minimal impact on utility.

C Dataset specifics

Table 4: Statistics of the datasets. Adapted from Luo et al. (2024)

Dataset	Pokec-z	Pokec-n	DBLP
# of nodes	67,796	66,569	20,111
# of edges	617,958	517,047	57,508
feature dim.	276	265	2530
# of labeled nodes	10,262	8,797	3,196
homophily rate	0.95	0.96	0.79
minority rate	0.35	0.29	0.18

D Synthetic dataset configuration

D.1 Graph generation

First, the number of nodes N was set, and a proportion f_m of these nodes was randomly assigned to the minority group, while the remainder formed the majority group. Each node received an activity score derived from a power-law distribution, parameterized separately for the majority (γ_M) and minority (γ_m) groups, reflecting their differential levels of connectivity potential.

Edges were created iteratively until the desired edge density d was achieved. For each iteration, a source node v_i was selected according to its activity level, and a target node v_j was chosen with a probability proportional to the product of its in-degree k_j^{in} and the homophily h_{ij} between the source and target. The homophily values h_{MM} and h_{mm} governed the likelihood of intra-group connections for the majority and minority groups, respectively. The expected number of edges in the graph was scaled by the parameter d, ensuring that the total number of edges approximated $d \times N \times (N-1)$.

D.2 Experimental settings

Multiple combinations of homophily rates and minority fractions were explored. Exploration ranges are based on the ranges used in the original paper (Espín-Noboa et al., 2022), as well as explorations by Ferrara et al. (2022).

The homophily values among majorities h_{MM} and minorities h_{mm} were sampled from the set $\{0.0, 0.1, 0.2, \ldots, 1.0\}$, while the fraction of minority nodes f_m was set to $\{0.1, 0.3, 0.5\}$. For each combination of these parameters, networks were generated and analyzed under fixed conditions.

The following parameters were held constant across all experiments. The number of nodes was set to $N = 2000$, and the edge density d was maintained at 0.0015, ensuring sparse graphs suitable for modeling real-world networks. The node activity followed a power-law out-degree distribution with parameters $\text{plo}_M = \text{plo}_m = 2.5$, reflecting heterogeneous connectivity patterns across groups. The number of feature dimensions needed for the proxy task was set to $n = 100$. Finally, all NIFA attacks were conducted using a perturbation rate of 1%, as per the original paper.

E Results from the original paper

Table 5: Original authors' attack performance of NIFA on different victim GNN models. The results are reported in percentage (%). Adapted from Luo et al. (2024).

		Pokec-z			**Pokec-n**			**DBLP**		
		Accuracy	Δ_{SP}	Δ_{EO}	Accuracy	Δ_{SP}	Δ_{EO}	Accuracy	Δ_{SP}	Δ_{EO}
GCN	Before	71.22 ± 0.28	7.13 ± 1.21	5.10 ± 1.28	70.92 ± 0.66	0.88 ± 0.62	2.44 ± 1.37	95.88 ± 1.61	3.84 ± 0.34	1.91 ± 0.75
	After	70.50 ± 0.30	**17.36 ± 1.16**	**15.59 ± 1.08**	70.12 ± 0.37	**10.10 ± 2.10**	**9.85 ± 1.97**	93.37 ± 1.48	**13.49 ± 2.83**	**20.33 ± 3.82**
GraphSAGE	Before	70.79 ± 0.62	4.29 ± 0.84	3.46 ± 1.12	68.77 ± 0.34	1.65 ± 1.31	2.34 ± 1.04	96.58 ± 0.29	4.27 ± 1.09	2.78 ± 0.91
	After	70.05 ± 1.25	**6.20 ± 1.63**	**4.20 ± 1.77**	68.93 ± 1.19	**3.32 ± 1.88**	**3.56 ± 1.91**	93.92 ± 0.74	**10.16 ± 2.24**	**16.65 ± 3.30**
APPNP	Before	69.79 ± 0.42	6.83 ± 1.25	5.07 ± 1.26	68.73 ± 0.64	3.39 ± 0.28	3.71 ± 0.28	96.58 ± 0.38	3.98 ± 1.18	2.20 ± 1.08
	After	67.83 ± 0.70	**18.44 ± 1.41**	**16.85 ± 1.50**	67.90 ± 0.76	**13.47 ± 3.22**	**13.52 ± 3.56**	92.46 ± 0.94	**13.88 ± 3.20**	**20.20 ± 4.25**
SGC	Before	69.09 ± 0.99	7.28 ± 1.50	5.45 ± 1.42	66.95 ± 1.69	2.74 ± 0.85	3.21 ± 0.78	96.53 ± 0.48	4.70 ± 1.26	3.11 ± 1.24
	After	67.83 ± 0.70	**17.65 ± 1.01**	**16.09 ± 1.06**	66.72 ± 1.21	**10.59 ± 2.40**	**10.67 ± 2.61**	92.56 ± 1.09	**13.88 ± 3.37**	**20.25 ± 4.44**
FairGNN	Before	68.75 ± 1.12	1.89 ± 0.63	1.51 ± 0.47	69.41 ± 0.66	1.42 ± 0.35	2.32 ± 0.57	93.12 ± 1.23	1.95 ± 0.99	3.09 ± 1.81
	After	69.38 ± 2.07	**5.71 ± 2.52**	**4.22 ± 1.89**	69.97 ± 0.42	**6.13 ± 5.81**	**6.33 ± 5.77**	92.56 ± 1.49	**5.89 ± 2.52**	**10.48 ± 3.82**
FairVGNN	Before	68.57 ± 0.45	3.79 ± 0.51	2.59 ± 0.59	67.77 ± 1.00	1.90 ± 1.23	3.10 ± 1.20	95.18 ± 0.54	1.90 ± 0.52	2.91 ± 1.05
	After	67.65 ± 0.38	**11.01 ± 2.79**	**9.28 ± 2.87**	65.74 ± 1.42	**3.51 ± 1.51**	**3.65 ± 1.56**	91.56 ± 1.13	**7.96 ± 1.49**	**13.57 ± 2.57**
FairSIN	Before	67.33 ± 0.22	1.73 ± 1.49	2.61 ± 1.44	67.18 ± 0.30	0.39 ± 0.89	2.40 ± 1.02	94.72 ± 0.62	0.23 ± 0.15	0.45 ± 0.16
	After	66.55 ± 0.44	**9.48 ± 2.62**	**10.39 ± 1.06**	66.20 ± 0.12	**11.82 ± 0.75**	**14.58 ± 0.22**	92.46 ± 0.32	**10.90 ± 2.12**	**23.65 ± 7.77**

Table 6: Original authors' Accuracy and Fairness performance of attack launched by the different attackers. The results are reported in percentage (%). Adapted from Luo et al. (2024)

	Pokec-z			**Pokec-n**			**DBLP**		
	Accuracy	Δ_{SP}	Δ_{EO}	Accuracy	Δ_{SP}	Δ_{EO}	Accuracy	Δ_{SP}	Δ_{EO}
Clean	71.22 ± 0.28	7.13 ± 1.21	5.10 ± 1.28	70.92 ± 0.66	0.88 ± 0.62	2.44 ± 1.37	95.88 ± 1.61	3.84 ± 0.34	1.91 ± 0.75
AFGSM	67.01 ± 0.24	3.07 ± 1.67	3.45 ± 0.22	68.21 ± 0.23	5.35 ± 0.15	5.68 ± 0.14	95.38 ± 0.30	5.44 ± 3.48	2.78 ± 0.41
TGDIA	62.20 ± 0.04	1.66 ± 0.16	0.77 ± 0.10	63.57 ± 0.08	7.28 ± 0.35	6.95 ± 0.34	93.42 ± 0.29	0.93 ± 0.70	1.82 ± 0.87
G^2A2C	39.41 ± 0.94	6.89 ± 0.91	6.11 ± 0.48	34.30 ± 1.71	2.23 ± 1.40	3.76 ± 1.04	86.28 ± 0.25	4.21 ± 0.66	3.80 ± 0.42
FA-GNN	69.80 ± 0.48	6.62 ± 1.21	8.67 ± 1.28	70.80 ± 0.97	2.64 ± 0.76	3.45 ± 0.54	95.48 ± 0.48	3.32 ± 1.65	8.74 ± 1.23
FATE	-	-	-	-	-	-	94.87 ± 0.41	3.62 ± 1.49	2.12 ± 1.01
G-FairAttack	-	-	-	-	-	-	95.12 ± 0.38	6.80 ± 0.59	2.94 ± 1.10
NIFA	70.50 ± 0.30	**17.36 ± 1.16**	**15.59 ± 1.08**	70.12 ± 0.37	**10.10 ± 2.10**	**9.85 ± 1.97**	93.37 ± 1.48	**13.49 ± 2.83**	**20.33 ± 3.82**

F Exploratory analysis

This section presents an exploratory analysis investigating how varying levels of homophily and minority group fractions influence fairness outcomes under NIFA. Changes in graph homophily could lead to systematic variations in fairness metrics Δ_{SP} and Δ_{EO}, offering insights into NIFA's effectiveness under diverse

conditions. The analysis considered previously mentioned configurations of homophily rates and minority group fractions. By varying the minority representation within the graphs, the goal was to identify consistent gradients in fairness metrics and possible interactions with the size of the minority fraction.

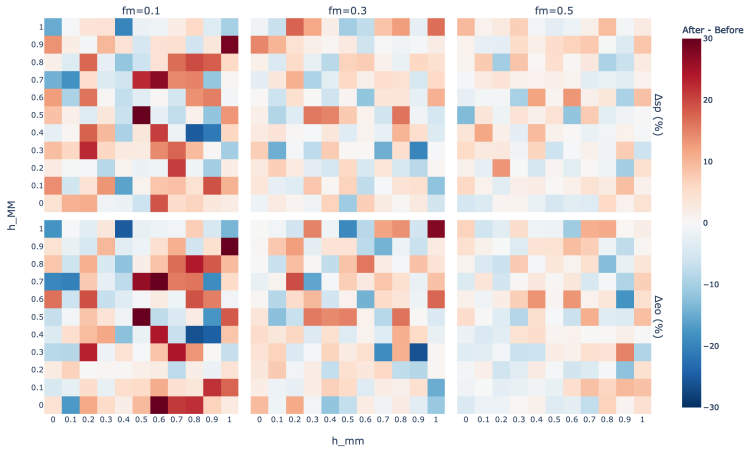

Figure 4: Impact of homophily and minority fraction on fairness metrics under NIFA.

The results, shown in Figure 4, did not reveal consistent patterns of Δ_{SP} and Δ_{EO} varying systematically with homophily levels before and after the attack. However, the metrics showed notable sensitivity to the minority fraction, with smaller fractions leading to larger differences. This indicates that minority representation could impact the magnitude of fairness shifts. Although preliminary, these findings show the importance of further investigation into the interaction between minority fraction and fairness metrics. For now, this analysis provides a foundation for continued exploration of the links between homophily, group representation, and fairness under adversarial interventions.