FeatWalk: A Feature-Aware Random Walk for Enhancing Individual Fairness in Graph Embeddings

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September 7, 2025

Abstract

Recent advancements in graph representation learning have highlighted the importance of fairness. However, existing methods such as CrossWalk and FairWalk primarily focus on group fairness, ensuring equitable outcomes across predefined populations, while often neglecting individual fairness, which demands that similar individuals receive similar outcomes. This report introduces **FeatWalk**, a novel random walk-based node representation learning algorithm designed to enhance individual fairness. FeatWalk modifies the random walk sampling process by incorporating node feature similarity as a bias. This encourages walks to traverse nodes that are not only structurally proximate but also similar in their attributes. We conduct extensive experiments on five real-world datasets (Bail, Facebook, NBA, Oklahoma, and German Credit). Our results demonstrate that FeatWalk significantly improves individual fairness metrics compared to state-of-the-art baselines. We also observe a corresponding increase in model accuracy in most cases. This improvement in individual fairness reveals an inherent trade-off with group fairness metrics, which we analyze and discuss. Our work underscores the importance of considering feature information for achieving a more nuanced and individual-level fairness in graph-based machine learning tasks.

1 Introduction

Graph representation learning has become a cornerstone of modern machine learning, enabling powerful analysis of networked data in domains from social media to biology [1]. Algorithms like DeepWalk [3] and Node2Vec [4] learn low-dimensional embeddings of nodes that preserve network structure, which can then be used for downstream tasks like node classification and link prediction.

As these algorithms are increasingly deployed in high-stakes applications, ensuring their fairness has become a critical concern [5]. A significant body of work has focused on mitigating bias in graph algorithms. Among these, methods like CrossWalk [1] and FairWalk [6] have emerged as effective techniques for enhancing **group fairness**. They operate by biasing the random walk process to mitigate disparities between demographic groups.

However, a sole focus on group fairness can obscure fairness violations at a finer granularity. An algorithm can be fair at the group level while still treating similar individuals differently, a concept known as **individual fairness** [7]. For instance, two individuals with nearly identical qualifications and network positions should receive similar predictions, regardless of their group affiliations. Existing random walk methods, which rely primarily on graph topology and group labels, do not explicitly optimize for this notion of fairness.

This report addresses this gap by proposing **FeatWalk**, a novel fairness-enhanced node representation learning method. FeatWalk builds upon the idea of biased random walks but introduces a new dimension: **node feature similarity**. The core idea is to guide the random walks not only based on structure but also towards nodes with similar feature vectors. This directly encourages the model to learn similar embeddings for similar nodes, thereby promoting individual fairness.

Our contributions are as follows:

- We propose **FeatWalk**, a new algorithm that biases random walks based on node feature similarity to enhance individual fairness.
- We conduct a comprehensive experimental evaluation on five datasets, demonstrating that FeatWalk significantly outperforms CrossWalk and FairWalk on individual fairness metrics.
- We analyze the inherent trade-off between individual and group fairness, showing how optimizing for one can negatively impact the other.

2 Related Work

Group Fairness in Graph Embeddings

Fairness in machine learning is broadly categorized into group and individual fairness. Group fairness aims to ensure that outcomes are statistically similar across different protected groups. In graph embeddings, this has been the primary focus.

CrossWalk [1] and **FairWalk** [6] are two prominent methods that enhance group fairness by modifying the random walk process to ensure more diverse neighborhood sampling across different demographic groups. Their interventions are based on group labels and network topology, but they are agnostic to the intrinsic attributes of the nodes, which is insufficient for guaranteeing individual fairness.

Individual Fairness

Individual fairness stipulates that similar individuals should be treated similarly [7]. In the context of graph embeddings, this translates to the principle that if two nodes are similar in their features, their learned embeddings should also be close in the vector space.

The paper **INFORM** by Kang et al. provides a principled study of this concept for graph mining, framing it within the Lipschitz property [2]. The core idea is that the "distance" between the outputs (embeddings) for two nodes should be bounded by the distance between their inputs (features). Formally, if $u \approx v$ in feature space, then $\Phi(u) \approx \Phi(v)$ in embedding space. The metric used to quantify this in our work, and inspired by this line of research, involves identifying for each node its k-nearest neighbors in the feature space and then measuring their average distance in the learned embedding space. A lower average distance signifies better adherence to individual fairness.

While both INFORM and FeatWalk share the goal of enhancing individual fairness, their approaches differ. INFORM proposes general frameworks that modify the model's objective function with a regularization term or post-process the results [2]. In contrast, **FeatWalk intervenes at the data generation stage** by altering the random walks themselves to be inherently sensitive to feature similarity, making it a specialized pre-processing technique for the DeepWalk/Node2Vec family of algorithms, whereas INFORM offers a more general, model-centric optimization framework applicable to a broader range of graph mining tasks.

3 Our Method: FeatWalk

The motivation behind FeatWalk is to create a node embedding algorithm that is sensitive to the individual characteristics of nodes, not just their group membership or structural role. While methods like CrossWalk focus on group-level adjustments, they may inadvertently separate nodes that are structurally distant but share similar features. FeatWalk addresses this by directly incorporating feature similarity into the walk generation process.

The core of our method is a modified random walk sampling strategy. For a walk currently at node u, the probability of transitioning to an adjacent node v is biased by the feature similarity between u and v. The transition weight w_{uv} is defined as:

$$w_{uv} = 1 + \alpha \cdot \mathrm{sim}(\mathbf{x}_u, \mathbf{x}_v)$$

where $\mathbf{x}_u$ and $\mathbf{x}_v$ are the feature vectors of nodes u and v, $\mathrm{sim}(\cdot,\cdot)$ is the cosine similarity, and α is a hyperparameter that controls the strength of the feature bias. When $\alpha = 0$, FeatWalk reduces to a standard un-biased random walk. For $\alpha > 0$, the walk is more likely to transition to neighbors with higher feature similarity.

The overall process is outlined in Algorithm 1. After the corpus of walks is generated, it is fed into a standard Word2Vec model to learn the final node embeddings.

Algorithm 1 FeatWalk Walk Generation

Input: Graph $G = (V, E)$, Node features X, Walk length L, Number of walks N_w, Bias factor α.
Output: A collection of walks $\mathcal{W}$.
Pre-compute similarity matrix $\mathbf{S}$ where $S_{uv} = \mathrm{sim}(\mathbf{x}_u, \mathbf{x}_v)$.
Initialize $\mathcal{W} \leftarrow \emptyset$.
for $i = 1$ to N_w **do**
  for each node $u \in V$ **do**
    Initialize walk $W \leftarrow [u]$.
    while $|W| < L$ **do**
      $curr \leftarrow W[-1]$.
      $\mathcal{N}(curr) \leftarrow$ Neighbors of $curr$.
      if $\mathcal{N}(curr)$ is empty **then break**
      end if
      Initialize weights $w \leftarrow []$.
      for each neighbor $v \in \mathcal{N}(curr)$ **do**
        Append $1 + \alpha \cdot S_{curr,v}$ to w.
      end for
      Normalize w to get probabilities P.
      Sample $next\_node$ from $\mathcal{N}(curr)$ using P.
      Append $next\_node$ to W.
    end while
    Add W to $\mathcal{W}$.
  end for
end for
return $\mathcal{W}$.

4 Contributions & Results

We evaluate FeatWalk on a node classification task and compare its performance against CrossWalk and FairWalk.

Datasets

We use five publicly available datasets with node features and sensitive attributes, loaded using the data loaders from the **PyGDebias** library. The original repository for this library can be found at `https://github.com/yushundong/PyGDebias`.

- **Bail:** A graph related to criminal recidivism prediction.
- **Facebook:** A social network graph where nodes represent users.
- **NBA:** A graph of NBA players with attributes related to their performance.

- **German Credit:** A graph of 1,000 bank clients, connected based on the similarity of their credit accounts.
- **Oklahoma:** A graph where sensitive attributes were synthetically generated. It is important to note that for this dataset, the provided data loader generates random labels; therefore, accuracy scores are not meaningful, but the fairness metrics still provide insight into the algorithms' behavior.

Evaluation Metrics

We use the following metrics to evaluate the algorithms:

- **Accuracy:** Standard classification accuracy on a downstream task.
- **Individual Fairness (IF) Score:** The average distance in the embedding space between each node and its k-nearest neighbors from the feature space. **Lower is better**.
- **Statistical Parity (SP):** The difference in the rate of positive outcomes between protected and unprotected groups. **Closer to 0 is better**.
- **Equal Opportunity (EO):** The difference in true positive rates between protected and unprotected groups. **Closer to 0 is better**.

Results and Discussion

The experimental results, summarized in Tables 1 through 5, provide a comprehensive view of FeatWalk's performance. A detailed analysis reveals three key findings.

First and foremost, FeatWalk is highly successful at its primary objective of enhancing individual fairness. Across all five datasets, it achieves the lowest (best) IF Score by a significant margin. For example, on the Bail dataset (Table 1), FeatWalk reduces the IF Score to 9.2197, which is less than half of the next best baseline, FairWalk (19.8272). This demonstrates that biasing random walks based on feature similarity is an effective strategy for ensuring that similar nodes receive similar embeddings.

Second, contrary to the common assumption that fairness interventions degrade performance, FeatWalk often improves model accuracy. On four out of the five datasets, FeatWalk achieves the highest accuracy. For instance, on the NBA dataset (Table 3), it increases accuracy to 0.6620, a substantial improvement over both CrossWalk (0.5399) and FairWalk (0.5258). This suggests that by guiding the embedding process to focus on salient node features, our method can capture local patterns that are not only fairer but also more predictive for the downstream task.

Third, the results highlight a critical trade-off between individual and group fairness. While FeatWalk shows strong performance on individual fairness, its impact on group fairness metrics (SP and EO) is mixed. On some datasets like Facebook (Table 2), it improves both individual and group fairness simultaneously. However, the German Credit dataset (Table 4) tells a different story: FeatWalk achieves the best IF Score but significantly worsens group fairness, with the SP score rising to 0.4154. This confirms our hypothesis that an algorithm narrowly focused on treating similar individuals alike may learn to ignore systemic, group-level disparities, which is a crucial consideration for practitioners.

Table 1: Algorithm Comparison on Bail Dataset

Algorithm	**Acc.**	**IF Score**	**SP**	**EO**
CrossWalk	0.5289	36.1532	0.0118	0.0229
FairWalk	0.8784	19.8272	0.0441	0.0069
FeatWalk	**0.7309**	**9.2197**	**0.0423**	**0.0000**

Table 2: Algorithm Comparison on Facebook Dataset

Algorithm	**Acc.**	**IF Score**	**SP**	**EO**
CrossWalk	0.6923	19.5608	0.0713	0.0275
FairWalk	0.6923	15.2386	0.0619	0.0394
FeatWalk	**0.7500**	**7.5589**	**0.0260**	**0.0000**

Table 3: Algorithm Comparison on NBA Dataset

Algorithm	**Acc.**	**IF Score**	**SP**	**EO**
CrossWalk	0.5399	8.7920	0.0120	0.0744
FairWalk	0.5258	10.8136	0.0762	0.1691
FeatWalk	**0.6620**	**5.3064**	**0.0294**	**0.0917**

Table 4: Algorithm Comparison on German Dataset

Algorithm	**Acc.**	**IF Score**	**SP**	**EO**
CrossWalk	0.5800	14.0620	0.1095	0.0536
FairWalk	0.5720	10.2148	0.0097	0.0000
FeatWalk	**0.6040**	**8.5196**	**0.4154**	**0.3950**

Table 5: Algorithm Comparison on Oklahoma Dataset

Algorithm	**Acc.**	**IF Score**	**SP**	**EO**
CrossWalk	0.8104	19.2576	0.0008	0.0195
FairWalk	0.8625	13.1088	0.0143	0.2857
FeatWalk	**0.9071**	**6.8211**	**0.0000**	**0.0000**

5 Challenges and Limitations

An important part of this project was not only developing a new method but also understanding its boundaries and the challenges encountered. We believe a transparent discussion of these aspects is crucial for a complete project report.

Instability of Results with Limited Walks

During our experiments with the **Bail dataset**, we observed that metrics like accuracy showed high variance across different runs. The primary reason for this instability was the **computational overhead** of FeatWalk. Since transition probabilities are calculated dynamically at each step, generating a large corpus of walks was time-consuming. With a limited number of walks, the resulting embeddings may not fully converge, making downstream task performance less reliable. While the trend for improved individual fairness remained strong, this experience highlights that for robust results, our method requires significant computational resources.

The Explicit Trade-off with Group Fairness

Our hypothesis was that focusing on individual fairness might negatively impact group fairness, and the results on the **German Credit dataset** starkly confirmed this. As shown in Table 4, while FeatWalk achieved the best IF Score, its group fairness metrics (SP and EO) were considerably worse than the baselines. The reason for this is fundamental to the algorithm's design. By biasing walks towards feature-similar nodes, FeatWalk may reduce the exploration of diverse, inter-group regions of the graph. This is not a failure, but a critical finding: **there is often a direct, quantifiable trade-off between different notions of fairness**.

Fundamental Dependency on Feature Quality

Finally, the entire premise of FeatWalk rests on the availability of high-quality, meaningful node features. If a graph has no features, or if the features are noisy and uncorrelated with the task, our method offers no advantage. In such cases, the feature similarity signal would be random noise, potentially harming the embedding quality compared to purely structural methods. This makes FeatWalk a specialized tool, highly effective in feature-rich environments.

6 Conclusion & Future Work

In this report, we addressed the limitations of existing fairness-aware graph embedding methods by shifting the focus from group-level to individual-level fairness. Our proposed algorithm, FeatWalk, effectively leverages node features to ensure that similar individuals are represented similarly in the embedding space.

However, as detailed in our challenges section, our work also highlights key limitations. The computational overhead, the explicit trade-off with group fairness, and the dependency on feature quality are important considerations.

Future work could explore several promising directions. First, developing more efficient algorithms for calculating feature-based biases could mitigate the computational cost. Second, creating hybrid models that allow for explicit tuning of the balance between individual and group fairness would provide greater flexibility. Finally, extending this feature-aware approach to other models, such as Graph Neural Networks (GNNs), could further advance the development of fair and accurate graph-based systems.

GitHub Repository

The Python implementation of our algorithm and the experiments are publicly available at our GitHub repository: `https://github.com/EmadEJ/FeatWalk`

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