On Generalized Degree Fairness in Graph Neural Networks

Zemin Liu, Trung-Kien Nguyen, Yuan Fang

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Motivation

Problem

Degree Fairness in GNNs

• Source: Neighborhood structure (degree)
• Outcome: Differential node behaviors and biased outcomes
• Goal: Achieve equitable outcomes for nodes of different degrees

Problem Formulation

Generalized degree

• Source of degree bias: Neighborhood and local context
• Local context: \( C_r = \{ v' \in V \mid d(v, v') \leq r \} \)
• Generalized degree \( \deg_r(v) = |A^r|_v \)

Generalized degree fairness

• Groups: \( G_i = \{ v \in V \mid d_i = \deg_r(v) < d_{i+1} \} \)
• Metrics
  - Degree Statistical Parity: \( P(y_i = y \mid v \in G_i) = P(y_i = y \mid v \in G_{i+1}) \)
  - Degree Equal Opportunity: \( P(y_i = y \mid v \in G_i) = P(y_i = y \mid v \in G_{i+1}) \)

Proposed model: DegFairGNN

Structural Contrast

Comprehensiveness

Context Embedding: \( c_i = \text{Pool}(\{h_i^k \mid w \in C_r(v)\}) \)

Debiasing Function: \( f(c_i, \theta_f) \)

Adaptiveness

\( D(v; \theta_d) = (\gamma + 1) \cdot (c_i(v) + \beta_0 \cdot \gamma^i \cdot \phi_0(\theta_d(v); \theta_s)) \)

\( \phi_0(\theta_d(v); \theta_s) = \phi(\theta_d(v); \theta_s)(\gamma(v) = \text{deg}(v)/10000 \gamma(v)) \)

Modulated GNN Encoder

\( h_i = \phi(\text{AGOR}(h_i^k \mid W \in N_i; \omega)) \)

\( + \epsilon \cdot (\lambda \cdot v_i^d \cdot D(v; \theta_d) + \mu \cdot v_i^s \cdot D(v; \theta_d)) \)

Overall Loss

\( L = L_1 + \mu L_2 + \lambda (L_3 + L_4) \)

Datasets

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Nodes</th>
<th>Edges</th>
<th>Features</th>
<th>Classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chameleon</td>
<td>2,277</td>
<td>31,371</td>
<td>2,325</td>
<td>5</td>
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<tr>
<td>Squirrel</td>
<td>5,201</td>
<td>198,353</td>
<td>2,089</td>
<td>5</td>
</tr>
<tr>
<td>EMNLP</td>
<td>2,600</td>
<td>7,969</td>
<td>8</td>
<td>2 (citation count)</td>
</tr>
</tbody>
</table>

Main results

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<tr>
<th></th>
<th>GCN</th>
<th>DSGCN</th>
<th>Residual2Vec</th>
<th>Tail-GNN</th>
<th>FairWalk</th>
<th>CPC</th>
<th>FairGNN</th>
<th>FairAdj</th>
<th>FairVGGN</th>
<th>DegFairGNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chameleon</td>
<td>0.62±0.05</td>
<td>0.60±0.10</td>
<td>0.60±0.10</td>
<td>0.60±0.10</td>
<td>0.59±0.10</td>
<td>0.63±0.08</td>
<td>0.63±0.07</td>
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<td>0.63±0.07</td>
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<tr>
<td>Squirrel</td>
<td>0.86±0.02</td>
<td>0.84±0.02</td>
<td>0.85±0.02</td>
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</tbody>
</table>

Ablation study

- (a) No scale and shift: worse in accuracy and fairness
- (b) No constraint: fairness generally becomes worse
- (c) No modulation: fairness becomes worse in most cases

Experiments

• Problem
  - Degree fairness in graph neural networks
• Proposed model: DegFairGNN
  - Target the root of degree bias
  - Flexibly work with most modern GNNs
• Experiments
  - Extensive experiments on three benchmark datasets shows promising results on both accuracy and fairness metrics

References


Acknowledgments

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