On Generalized Degree Fairness in Graph Neural Networks

Zemin Liu, Trung-Kien Nguyen, Yuan Fang

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Outline

• Problem & related work
• Proposed model: DegFairGNN
• Experiments
• Conclusions
Graph Representation Learning

• Graph embedding approaches
  – DeepWalk [1], node2vec [2], …

• Graph neural networks (GNNs) [3,4,5]

\[ h^l_v = \mathcal{M}(h^{l-1}_v, \{h^{l-1}_i : i \in \mathcal{N}_v\}; \theta^l) \]

Fairness vs Degree Fairness in GNNs

• Fairness in GNNs
  – Source
    • Sensitive attributes (e.g., gender, age, or race)
  – Some related methods
    • Filters to debias: CFC [1]
    • Adversarial learning paradigm: [1,2]

• Degree Fairness in GNNs
  – Source
    • Neighborhood structure (degree)
  – Outcome
    • Differential node behaviors and biased outcomes
  – Goal
    • Achieve equitable outcomes for nodes of different degrees

Degree Fairness in GNNs

• Our goal
  – Degree fairness in graph neural networks

• Non-trivial
  – Neighborhood sampling
    • Cannot address this issue
    • Information loss
  – Degree vs sensitive attributes
    • Prior works do not debias neighborhood aggregation
Problem Formulation (1): \textit{generalized degree}

- Generalized degree
  - Source of degree bias
    - Neighborhood & local context
  - Local context
    \[
    C_r = \{ v' \in V \mid d(v, v') \leq r \}
    \]
  - Generalized degree
    \[
    \deg_r(v) = [A^r 1]_v
    \]
Problem Formulation (2): *generalized degree fairness*

- Generalized degree fairness (Statistical Parity [1] and Equal Opportunity [2])
  - Generalized degree groups
    - $m$ groups: $G_1, \ldots, G_m$
    \[
    G_i = \{v \in V \mid d_i \leq \deg_r(v) < d_{i+1}\}
    \]
  - Generalized degree metrics
    - Degree Statistical Parity (DSP)
      \[
      P(\hat{y}_v = y \mid v \in G_i) = P(\hat{y}_v = y \mid v \in G_j)
      \]
    - Degree Equal Opportunity (DEO)
      \[
      P(\hat{y}_v = y \mid y_v = y, v \in G_i) = P(\hat{y}_v = y \mid y_v = y, v \in G_j)
      \]

Outline

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• Experiments
• Conclusions
DegFairGNN: overall framework

(a) Toy graph  (b) Structural contrast  (c) Debiasing neighborhood aggregation  (d) Overall objective
Structural Contrast

- **Contrastive strategy**
  - Low-degree nodes $\mathcal{S}_0$ and high-degree nodes $\mathcal{S}_1$
  - Neighborhood aggregation
    - Only access its one-hop contexts in each layer
  - Definition of the two groups
    \[
    \mathcal{S}_0 = \{ v \in \mathcal{V} \mid \deg_1(v) \leq K \}
    \]
    \[
    \mathcal{S}_1 = \mathcal{V} \setminus \mathcal{S}_0
    \]
Debiasing Neighborhood Aggregation (1)

- **Debiasing function**
  - Low-degree node
    \[ u \in S_0, \mathcal{D}(u; \theta_0^l) \in \mathbb{R}^{d_l} \]
  - High-degree node
    \[ v \in S_1, \mathcal{D}(v; \theta_1^l) \in \mathbb{R}^{d_l} \]

- **Requirement of debiasing function**
  - Comprehensiveness
  - Adaptiveness

(c) Debiasing neighborhood aggregation
Debiasing Neighborhood Aggregation (2)

- **Comprehensiveness**
  - Context embedding
    \[ c_v^l = \text{POOL} (\{ h_u^{l-1} \mid u \in C_r(v) \}) \]
  - Debiasing function
    \[ D(v; \theta^l) = f (c_v^l; \theta^l_{c,*}) \]

- **Adaptiveness**
  \[ D(v; \theta^l) = (\gamma_v^l + 1) \odot f (c_v^l; \theta^l_{c,*}) + \beta_v^l \]
  \[ \gamma_v^l = \phi_\gamma (\delta^l(v); \theta_{\gamma}^l), \quad \beta_v^l = \phi_\beta (\delta^l(v); \theta_{\beta}^l) \]
  - Degree encoding
    \[ [\delta^l(v)]_{2i} = \sin(\text{deg}_1(v)/10000^{2i/d_l}) \]
    \[ [\delta^l(v)]_{2i+1} = \cos(\text{deg}_1(v)/10000^{2i/d_l}) \]

Degree encoding
Debiasing Neighborhood Aggregation (3)

- Modulated GNN Encoder

\[
\begin{align*}
h^l_v &= \sigma \left( \text{AGGR}(\{h^{l-1}_u \mid u \in N_v\}; \omega^l) \\
&\quad + \epsilon \cdot \left( I(v \in S_0) D(v; \theta_0^l) + I(v \in S_1) D(v; \theta_1^l) \right) \right)
\end{align*}
\]

Control the impact
Training Constraints and Objective

- Node classification loss
  \[ \mathcal{L}_1 = - \sum_{v \in \mathcal{V}^{tr}} \sum_{y=1}^{|\mathcal{Y}|} [y_v]_y \ln[h_v^l]_y \]

- Fairness loss
  \[ \mathcal{L}_2 = \left\| \frac{1}{|\mathcal{S}_0^{tr}|} \sum_{v \in \mathcal{S}_0^{tr}} h_v^l - \frac{1}{|\mathcal{S}_1^{tr}|} \sum_{v \in \mathcal{S}_1^{tr}} h_v^l \right\|_2^2 \]

- Constraints on debiasing contexts
  \[ \mathcal{L}_3 = \sum_{l=1}^{\ell} \left( \sum_{v \in \mathcal{S}_0^g} \|D(v; \theta_1^l)\|_2^2 + \sum_{v \in \mathcal{S}_1^{tr}} \|D(v; \theta_0^l)\|_2^2 \right) \]

- Constraints on scaling and shifting
  \[ \mathcal{L}_4 = \sum_{l=1}^{\ell} \sum_{v \in \mathcal{V}^{tr}} \left( \|\gamma_v^l\|_2^2 + \|\beta_v^l\|_2^2 \right) \]

- Overall loss
  \[ \mathcal{L} = \mathcal{L}_1 + \mu \mathcal{L}_2 + \lambda (\mathcal{L}_3 + \mathcal{L}_4) \]
Outline

- Problem & related work
- Proposed model: DegFairGNN
- Experiments
- Conclusions
Experimental setup

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 (traffic volume)</td>
</tr>
<tr>
<td>Squirrel</td>
<td>5,201</td>
<td>198,353</td>
<td>2,089</td>
<td>5 (traffic volume)</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>

Baselines

- Degree-specific models:
  - DSGCN [4], Residual2Vec [5], Tail-GNN [6]
- Fairness-aware models:
  - FairWalk [7], CFC [8], FairGNN [9], FairAdj [10], FairVGNN [11]

Base GNN models

- GCN [1]
- GAT [2]
- GraphSAGE [3]

References

Experimental setup

Evaluation Metrics for fairness

\[ \Delta_{DSP} = \frac{1}{|Y|} \sum_{y \in Y} \left| P(\hat{y}_v = y | v \in G_0) - P(\hat{y}_v = y | v \in G_1) \right|, \]

\[ \Delta_{DEO} = \frac{1}{|Y|} \sum_{y \in Y} \left| P(\hat{y}_v = y | y_v = y, v \in G_0) - P(\hat{y}_v = y | y_v = y, v \in G_1) \right|. \]
## Model Accuracy and Fairness

### Table 2: Comparison with baselines \((r = 1, 20\%\) Top/Bottom).\n
Henceforth, tabular results are in percent with standard deviation over 5 runs; the best fairness result is **bolded** and the runner-up is underlined.

<table>
<thead>
<tr>
<th></th>
<th>GCN</th>
<th>DSGCN</th>
<th>Residual2Vec</th>
<th>Tail-GNN</th>
<th>FairWalk</th>
<th>CFC</th>
<th>FairGNN</th>
<th>FairAdj</th>
<th>FairVGGN</th>
<th>DegFairGCN</th>
</tr>
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<tbody>
<tr>
<td>Chamel.</td>
<td></td>
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</tr>
<tr>
<td>Acc.</td>
<td>62.45 ± 0.21</td>
<td>63.90 ± 1.28</td>
<td>49.04 ± 0.01</td>
<td>66.08 ± 0.19</td>
<td>56.36 ± 0.75</td>
<td>63.02 ± 0.84</td>
<td>70.70 ± 0.52</td>
<td>51.71 ± 1.13</td>
<td>72.32 ± 0.50</td>
<td>69.91 ± 0.19</td>
</tr>
<tr>
<td>(\Delta_{DSP})↓</td>
<td>9.68 ± 1.37</td>
<td>8.81 ± 1.15</td>
<td>14.52 ± 0.69</td>
<td>8.51 ± 1.72</td>
<td>8.18 ± 0.93</td>
<td>10.12 ± 1.28</td>
<td>7.33 ± 1.09</td>
<td>9.79 ± 1.91</td>
<td>8.86 ± 1.11</td>
<td><strong>5.85 ± 0.32</strong></td>
</tr>
<tr>
<td>(\Delta_{DEO})↓</td>
<td>36.08 ± 2.65</td>
<td>25.14 ± 2.67</td>
<td>37.31 ± 1.99</td>
<td>26.09 ± 3.25</td>
<td>22.89 ± 2.75</td>
<td>29.54 ± 1.95</td>
<td>26.83 ± 1.95</td>
<td>27.48 ± 2.06</td>
<td>26.02 ± 2.39</td>
<td><strong>21.60 ± 0.71</strong></td>
</tr>
<tr>
<td>Squirrel</td>
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</tr>
<tr>
<td>Acc.</td>
<td>47.85 ± 1.33</td>
<td>40.71 ± 2.17</td>
<td>28.47 ± 0.01</td>
<td>42.62 ± 0.06</td>
<td>37.68 ± 0.65</td>
<td>45.64 ± 2.19</td>
<td>57.29 ± 0.77</td>
<td>35.18 ± 1.22</td>
<td>46.97 ± 0.48</td>
<td>59.21 ± 0.97</td>
</tr>
<tr>
<td>(\Delta_{DSP})↓</td>
<td>13.37 ± 2.83</td>
<td>16.08 ± 0.86</td>
<td>25.11 ± 0.48</td>
<td>18.91 ± 0.26</td>
<td><strong>7.94 ± 0.36</strong></td>
<td>12.40 ± 0.48</td>
<td>12.96 ± 1.03</td>
<td>16.63 ± 1.56</td>
<td>26.67 ± 0.52</td>
<td>9.54 ± 1.02</td>
</tr>
<tr>
<td>(\Delta_{DEO})↓</td>
<td>27.00 ± 3.79</td>
<td>32.61 ± 3.74</td>
<td>34.49 ± 0.72</td>
<td>33.60 ± 0.72</td>
<td>17.12 ± 1.50</td>
<td>21.60 ± 2.69</td>
<td>17.62 ± 2.40</td>
<td>27.54 ± 1.73</td>
<td>35.80 ± 1.76</td>
<td><strong>16.42 ± 1.38</strong></td>
</tr>
<tr>
<td>EMNLP</td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>Acc.</td>
<td>78.92 ± 0.43</td>
<td>82.19 ± 0.77</td>
<td>80.69 ± 0.01</td>
<td>83.72 ± 0.28</td>
<td>82.23 ± 0.18</td>
<td>80.15 ± 1.13</td>
<td>86.81 ± 0.22</td>
<td>76.50 ± 1.55</td>
<td>84.03 ± 0.34</td>
<td>79.92 ± 0.77</td>
</tr>
<tr>
<td>(\Delta_{DSP})↓</td>
<td>44.55 ± 1.90</td>
<td>50.00 ± 2.98</td>
<td>12.90 ± 0.15</td>
<td>41.18 ± 1.58</td>
<td>33.52 ± 1.46</td>
<td>56.60 ± 1.95</td>
<td>58.23 ± 1.44</td>
<td>40.38 ± 4.64</td>
<td>43.92 ± 1.43</td>
<td><strong>12.38 ± 3.72</strong></td>
</tr>
<tr>
<td>(\Delta_{DEO})↓</td>
<td>34.05 ± 3.56</td>
<td>46.92 ± 2.91</td>
<td>11.26 ± 0.67</td>
<td>36.76 ± 1.48</td>
<td>30.67 ± 1.42</td>
<td>45.21 ± 2.27</td>
<td>51.56 ± 1.38</td>
<td>41.89 ± 4.78</td>
<td>40.95 ± 1.71</td>
<td><strong>8.52 ± 2.26</strong></td>
</tr>
</tbody>
</table>

### Table 3: Comparison to baselines \((r = 2, 20\%\) Top/Bottom).\n
<table>
<thead>
<tr>
<th></th>
<th>GCN</th>
<th>FairWalk</th>
<th>FairGNN</th>
<th>DegFairGCN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chamel.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acc.</td>
<td>62.45 ± 0.21</td>
<td>56.36 ± 0.75</td>
<td>70.70 ± 0.52</td>
<td>69.91 ± 0.19</td>
</tr>
<tr>
<td>(\Delta_{DSP})↓</td>
<td>5.96 ± 0.89</td>
<td>10.38 ± 0.85</td>
<td>6.70 ± 0.32</td>
<td><strong>5.25 ± 0.39</strong></td>
</tr>
<tr>
<td>(\Delta_{DEO})↓</td>
<td>26.92 ± 2.09</td>
<td>25.46 ± 1.66</td>
<td>23.66 ± 0.93</td>
<td><strong>19.05 ± 0.74</strong></td>
</tr>
<tr>
<td>Squirrel</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acc.</td>
<td>47.85 ± 1.33</td>
<td>37.68 ± 0.65</td>
<td>57.29 ± 0.77</td>
<td>59.21 ± 0.97</td>
</tr>
<tr>
<td>(\Delta_{DSP})↓</td>
<td>14.61 ± 2.63</td>
<td>9.64 ± 0.50</td>
<td>11.11 ± 0.93</td>
<td><strong>8.26 ± 0.57</strong></td>
</tr>
<tr>
<td>(\Delta_{DEO})↓</td>
<td>28.62 ± 3.89</td>
<td>17.37 ± 1.10</td>
<td>16.29 ± 2.07</td>
<td><strong>14.95 ± 1.22</strong></td>
</tr>
<tr>
<td>EMNLP</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acc.</td>
<td>78.92 ± 0.43</td>
<td>82.23 ± 0.18</td>
<td>86.81 ± 0.22</td>
<td>79.92 ± 0.77</td>
</tr>
<tr>
<td>(\Delta_{DSP})↓</td>
<td>45.03 ± 1.77</td>
<td>34.80 ± 0.12</td>
<td>52.88 ± 1.39</td>
<td><strong>10.87 ± 4.00</strong></td>
</tr>
<tr>
<td>(\Delta_{DEO})↓</td>
<td>34.71 ± 3.31</td>
<td>31.11 ± 1.34</td>
<td>45.78 ± 1.36</td>
<td><strong>8.72 ± 2.17</strong></td>
</tr>
</tbody>
</table>

### Table 4: Comparison to baselines \((r = 1, 30\%\) Top/Bottom).\n
<table>
<thead>
<tr>
<th></th>
<th>GCN</th>
<th>FairWalk</th>
<th>FairGNN</th>
<th>DegFairGCN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chamel.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acc.</td>
<td>62.45 ± 0.21</td>
<td>56.36 ± 0.75</td>
<td>70.70 ± 0.52</td>
<td>69.91 ± 0.19</td>
</tr>
<tr>
<td>(\Delta_{DSP})↓</td>
<td>5.95 ± 1.02</td>
<td>8.16 ± 0.38</td>
<td>6.92 ± 0.29</td>
<td><strong>4.15 ± 0.02</strong></td>
</tr>
<tr>
<td>(\Delta_{DEO})↓</td>
<td>18.00 ± 1.76</td>
<td>16.65 ± 1.32</td>
<td>14.52 ± 1.09</td>
<td><strong>8.39 ± 0.37</strong></td>
</tr>
<tr>
<td>Squirrel</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acc.</td>
<td>47.85 ± 1.33</td>
<td>37.68 ± 0.65</td>
<td>57.29 ± 0.77</td>
<td>59.21 ± 0.97</td>
</tr>
<tr>
<td>(\Delta_{DSP})↓</td>
<td>10.34 ± 2.15</td>
<td><strong>6.17 ± 0.36</strong></td>
<td>9.27 ± 0.68</td>
<td>7.39 ± 0.63</td>
</tr>
<tr>
<td>(\Delta_{DEO})↓</td>
<td>22.62 ± 3.10</td>
<td><strong>14.97 ± 1.12</strong></td>
<td>17.42 ± 1.11</td>
<td>17.71 ± 1.05</td>
</tr>
<tr>
<td>EMNLP</td>
<td></td>
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</tr>
<tr>
<td>Acc.</td>
<td>78.92 ± 0.43</td>
<td>82.23 ± 0.18</td>
<td>86.81 ± 0.22</td>
<td>79.92 ± 0.77</td>
</tr>
<tr>
<td>(\Delta_{DSP})↓</td>
<td>42.87 ± 1.40</td>
<td>34.19 ± 0.91</td>
<td>48.25 ± 1.97</td>
<td><strong>14.46 ± 3.35</strong></td>
</tr>
<tr>
<td>(\Delta_{DEO})↓</td>
<td>37.89 ± 3.27</td>
<td>34.49 ± 0.91</td>
<td>48.83 ± 1.97</td>
<td><strong>10.92 ± 2.87</strong></td>
</tr>
</tbody>
</table>
Model Analysis

Table 5: With other base GNNs ($r = 1$, 20% Top/Bottom).

<table>
<thead>
<tr>
<th></th>
<th>GAT</th>
<th>DegFairGAT</th>
<th>GraphSAGE</th>
<th>DegFairSAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chamel.</td>
<td>Acc. ↑ 63.15 ± 0.40</td>
<td>69.64 ± 0.44</td>
<td>53.15 ± 0.56</td>
<td>60.95 ± 0.84</td>
</tr>
<tr>
<td></td>
<td>$\Delta_{DSP}$ ↓ 9.35 ± 1.61</td>
<td>7.88 ± 1.30</td>
<td>10.86 ± 0.74</td>
<td>8.22 ± 1.22</td>
</tr>
<tr>
<td></td>
<td>$\Delta_{DEO}$ ↓ 29.59 ± 1.43</td>
<td>26.12 ± 2.06</td>
<td>29.42 ± 1.57</td>
<td>26.40 ± 2.32</td>
</tr>
<tr>
<td>Squirrel</td>
<td>Acc. ↑ 41.44 ± 0.21</td>
<td>45.55 ± 1.44</td>
<td>34.39 ± 0.62</td>
<td>34.63 ± 1.31</td>
</tr>
<tr>
<td></td>
<td>$\Delta_{DSP}$ ↓ 12.60 ± 0.77</td>
<td>12.03 ± 0.63</td>
<td>5.39 ± 0.66</td>
<td>3.76 ± 0.23</td>
</tr>
<tr>
<td></td>
<td>$\Delta_{DEO}$ ↓ 24.89 ± 0.69</td>
<td>20.64 ± 3.06</td>
<td>17.13 ± 2.86</td>
<td>14.91 ± 1.35</td>
</tr>
<tr>
<td>EMNLP</td>
<td>Acc. ↑ 70.42 ± 0.77</td>
<td>81.57 ± 1.14</td>
<td>83.96 ± 0.31</td>
<td>83.57 ± 0.44</td>
</tr>
<tr>
<td></td>
<td>$\Delta_{DSP}$ ↓ 24.40 ± 3.06</td>
<td>14.11 ± 6.28</td>
<td>56.33 ± 1.12</td>
<td>28.43 ± 3.79</td>
</tr>
<tr>
<td></td>
<td>$\Delta_{DEO}$ ↓ 8.36 ± 1.29</td>
<td>12.28 ± 6.19</td>
<td>51.71 ± 0.88</td>
<td>24.65 ± 3.35</td>
</tr>
</tbody>
</table>

Additional Base GNNs
- Outperform their corresponding base GNNs

Ablation Study
- Without scaling and shifting
  - Worse accuracy and fairness
- Without structural contrast
  - Fairness generally become worse
- Without the modulation of aggregation
  - Fairness become worse in most cases

Figure 2: Ablation study on the effect of each module.
Outline

• Problem & related work
• Proposed model: DegFairGNN
• Experiments
• Conclusions
Conclusions

• **Problem**
  – Degree fairness in graph neural networks

• **Proposed model: DegFairGNN**
  – Target the root of degree bias
    • modulating the core operation of neighborhood aggregation through a structural contrast
  – Flexibly work with most modern GNNs

• **Experiments**
Thanks!

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