Introducing Fairness in Graph Visualization

Seok-Hee Hong, Giuseppe Liotta, Fabrizio Montecchiani,
Martin Nöllenburg, and Tommaso Piselli

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Motivation

- The presence of **bias** in decision support systems may worsen social inequalities and harm individuals.
- Identifying sources of **bias** and striving for **fairness** are crucial topics for the ethical use and development of AI.
- In a recent work, Peltonen et al. [1] state that **"*Fairness*** *should also extend to* ***visualization****, s.t. analysts are not driven to draw unfair conclusions while exploring data*."
- **Idea**: complement classical network visualization tools with new **fair visualizations** to reduce bias and avoid discrimination.
- We propose a novel research direction aimed at studying the topic of **fair network visualizations.**

Research Questions

Q1 (Price of Fairness)
How large is the stress increase to compute a minimally unfair straight-line drawing of a graph starting from a minimum stress layout?

Q2 (Unfairness of Globally Optimal Drawings)
How unfair are minimum stress straight-line drawings?

Model

- We formalize the notion of **fair straight-line graph drawings**, based on the **stress** metric, to introduce the concept of fairness in network visualizations.
- A **drawing Γ** of G maps each vertex $v \in V$ to a point of the Euclidean plane and each edge $e \in E$ to a straight-line segment connecting its endpoints.
- Stress minimization is an optimization strategy in **Multi-Dimensional Scaling (MDS)** and a widely adopted quality function in Graph Drawing [2].

$$stress(\Gamma) = \sum_{u,v \in V} \omega(u,v)\left(\|\Gamma(u) - \Gamma(v)\|_2 - \delta(u,v)\right)^2$$

- Our vertex set is the union of two distinct sets, i.e. $V_R \cup V_B = V$
  V_R are the red vertices - V_B are the blue vertices
- Then, we can define the stress of each set as:

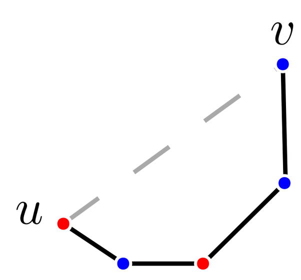
$$stress_R(\Gamma) = \sum_{u \in V_R, v \in V} \omega(u,v)\left(\|\Gamma(u) - \Gamma(v)\|_2 - \delta(u,v)\right)^2$$

$$stress_B(\Gamma) = \sum_{u \in V_B, v \in V} \omega(u,v)\left(\|\Gamma(u) - \Gamma(v)\|_2 - \delta(u,v)\right)^2$$

- To achieve a **fair visualization**, the difference between $stress_R(\Gamma)$ and $stress_B(\Gamma)$, normalized by their own cardinalities, should be as close as possible to **zero.**

- We define the **Unfairness λ** of a drawing Γ:

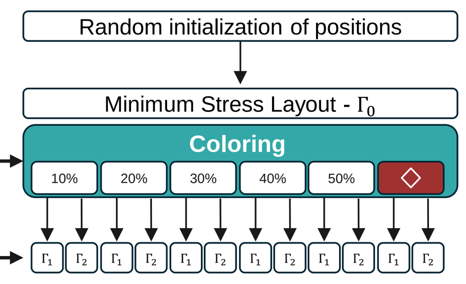
$$\lambda(\Gamma) = \left(\frac{stress_R(\Gamma)}{|V_R|} - \frac{stress_B(\Gamma)}{|V_B|}\right)^2$$



Experiments

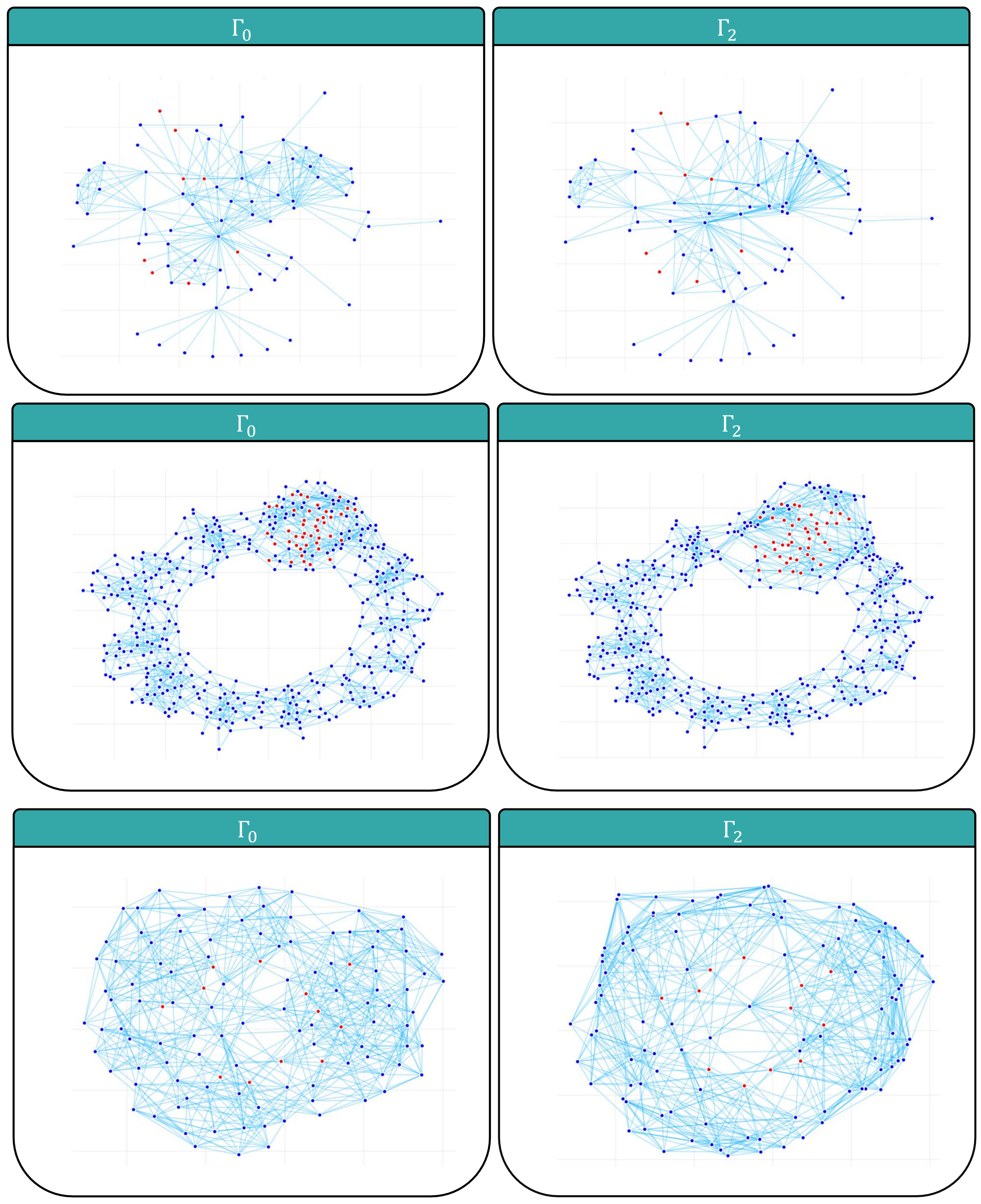
- Inspired by [3], we implemented a **Gradient-Descent** based algorithm to optimize multiple drawing criteria.
- First, it computes stress-minimum drawings (Γ_0), then it minimizes the unfairness by increasing the stress no more than 5% (Γ_1), and 20% (Γ_2).
- Benchmark **dataset**: constructed by selecting 30 graphs from the well-known Sparse Matrix Collection.
- Ranges: $|V| \in [100, 6000]$, $|E| \in [500, 14000]$

- **Number of drawings**
  30 graphs × 10 initializations × 6 colorings × 3 layouts



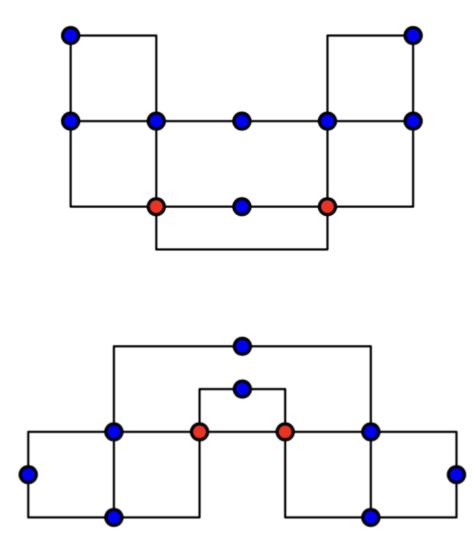
- For the experiments, we randomly colored a percentage p of vertices (red).
- The last coloring, ◇, refers to the scenario in which the red vertices are 10% of those with largest stress in Γ_0.
- The results are averaged over all drawings in the same group.

	Γ_0		Γ_1		Γ_2	
p	AVG STRESS	AVG UNFAIRNESS	AVG STRESS. VAR.	AVG UNFAIRNESS VAR.	AVG STRESS VAR.	AVG UNFAIRNESS VAR.
0.1	$6.31 \cdot 10^{-2}$	$1.46 \cdot 10^{-9}$	+0.57%	-96.2%	+0.77%	-97.9%
0.2	$6.31 \cdot 10^{-2}$	$6.08 \cdot 10^{-10}$	+0.43%	-94.1%	+0.46%	-94.5%
0.3	$6.31 \cdot 10^{-2}$	$4.77 \cdot 10^{-10}$	+0.34%	-92.9%	+0.38%	-93.9%
0.4	$6.31 \cdot 10^{-2}$	$4.51 \cdot 10^{-10}$	+0.34%	-92.5%	+0.38%	-93.4%
0.5	$6.31 \cdot 10^{-2}$	$3.40 \cdot 10^{-10}$	+0.28%	-92.2%	+0.29%	-92.2%
◇	$6.31 \cdot 10^{-2}$	$5.82 \cdot 10^{-8}$	+2.47%	-57.9%	+8.11%	-80.4%



Conclusions and future works

- Our experiments suggest that stress-minimum drawings may be suboptimal in terms of fairness, but incorporating fairness in the optimization process can effectively lead to notable improvements (Q2). Also, if one is willing to pay a small fraction of additional stress in the drawing, unfairness can be further minimized and brought down to almost zero (Q1).
- The concept of fairness can be studied for other graph drawing paradigms, such as orthogonal drawings, where one can consider the number of bends along the edges as a natural optimization criterion. In this regard, also challenging theoretical questions concerning the computational complexity of optimizing both fairness and bends can be addressed.



References:

[1] Peltonen, Jaakko and Xu, Wen and Nummenmaa, Timo and Nummenmaa, Jyrki - **Fair neighbor embedding** - *International Conference on Machine Learning (2023)*
[2] Gansner, Emden R and Koren, Yehuda and North, Stephen - **Graph drawing by stress majorization** - *Graph Drawing: 12th International Symposium (2004).*
[3] Ahmed, Reyan and De Luca, Felice and Devkota, Sabin and Kobourov, Stephen and Li, Mingwei- **Multicriteria Scalable Graph Drawing via Stochastic Gradient Descent** - *IEEE Transactions on Visualization and Computer Graphics (2022).*