9^{th} International Conference on Computational Social Science IC^2S^2
July 17-20, 2023, Copenhagen, Denmark

Quantifying and Reducing Marginalization in Networks: a Genetic Approach

feature-rich networks, marginalization, discrimination, fairness, genetic algorithms

Extended Abstract

The study of social discrimination and inequalities has long benefitted from network analysis tools. Methods from network science can characterize a wide variety of phenomena that exacerbate social exclusion and community segregation, among gender inequalities in science [4], racial discrimination in online social networks [5], and weight stigma in adolescents [6]. Moreover, they can quantify the structural effects of human and algorithmic biases [1, 2], and minority groups underrepresentation [3].

In this work, we tackle discrimination on social networks from a novel, different angle. We aim to quantify the extent to which an individual (e.g., a social media user) is marginalized by their peers according to a specific attribute (e.g., gender, age group, ethnicity). Marginalization, defined as the act of relegating someone or something to an unimportant position, is often based on individual characteristics, and can indeed occur between different groups (e.g., a non-white person marginalized by white people) or inside of the same group (e.g., a white person marginalized by other white people).

In a fair, non-discriminating society, similar individuals should receive similar treatment. This is sometimes known as individual fairness [7]. Such premise, when transposed to network topologies, implies that all nodes should be surrounded by a group of peers that manifests a similar distribution with respect to an attribute. Additionally, such distribution should be representative of the label distribution in the whole system. A proportionally-different distribution would indeed imply some sort of marginalization against the node – either by nodes with different labels or by those with the same label.

Moving from these simple assumptions, we propose two measures to quantify marginalization both at the micro-scale and macro-scale levels. At the node level, we introduce a measure that takes into account the attribute distribution in the node's neighborhood and compares it to the distribution in the whole network. This quantity, which we name Individual Marginalization Score (IMS), ranges in [-1, 1] and describes (i) marginalization perpetrated by nodes with the same attribute for $IMS < 0$, (ii) marginalization perpetrated by nodes with a different attribute for $IMS > 0$, and (iii) no marginalization for $IMS = 0$. We stipulate that a node can be considered marginalized if its absolute IMS is beyond a fixed threshold. At the macro-scale level, we introduce the System Marginalization Score (SMS), which captures the average marginalization for all nodes, regardless of the sign.

Moreover, we propose an algorithm in two phases that reduces marginalization by the means of an alteration strategy. The algorithm finds a combination of edges to be removed and/or added that minimizes the number of marginalized nodes with relatively limited modifications to the network. In order to prune the search space, in the first phase we leverage the triadic closure principle to carefully select potential new edges and weak removable edges. We assume that a non-existing edge that would close 10 triangles is more likely to appear than one that would close 2 triangles; conversely, an existing edge that closes 2 triangles is weaker (i.e., more likely to be removed) than one closing 10 triangles. Since different systems require different intervention strategies, we leave to the user the choice to (i) add and/or remove edges; (ii) assume

either a global point of view (that of an external entity that is aware of the marginalization of all individuals e.g., a recommendation system) or a local one (i.e., that of individuals that wish to overcome their marginalized status). Different alteration strategies (adding and/or removing connections) and points of view (global or local) produce different solutions which can be more or less suitable depending on the domain.
During the second phase, plausible and/or removable edges are encoded in a binary vector (see Figure 1). Starting from such a vector, the algorithm tries to minimize the discrimination (i.e., either the *SMS* or the number of discriminated nodes) via a genetic algorithm; if equal solutions are found, the one with fewer interventions is prioritized.
Preliminary results on the Copenhagen Networks Study Bluetooth interaction data [8] show that our approach is able to considerably reduce the number of marginalized nodes with relatively few new ties (see Figure 2). When compared to the random addition of the same number of edges on multiple simulations, the algorithm reduces nearly double the amount of discriminated nodes. We validated our result with a left-tailed hypothesis test ($\alpha = 0.05$).

References

[1] Lerman, K., Yan, X., & Wu, Z. (2016). The "Majority Illusion" in Social Networks. PLOS ONE, 11(2), e0147617.

[2] Sîrbu, A., Pedreschi, D., Giannotti, F., *et al.* (2019). Algorithmic bias amplifies opinion fragmentation and polarization: A bounded confidence model. PLOS ONE, 14(3), e0213246.

[3] Karimi, F., Oliveira, M., & Strohmaier, M. (2022). Minorities in networks and algorithms. ArXiv.

[4] Huang, J., Gates, A. J., Sinatra, R., *et al.*, (2020). Historical comparison of gender inequality in scientific careers across countries and disciplines. *Proceedings of the National Academy of Sciences*, 117(9), 4609-4616.

[5] Nguyen, H., Gokhale, S.S. Analyzing extremist social media content: a case study of Proud Boys. *Soc. Netw. Anal. Min.* 12, 115 (2022).

[6] Arias Ramos, N., Calvo Sánchez, M. D., Fernández-Villa, T., *et al.*(2018) Social exclusion of the adolescent with overweight: study of sociocentric social networks in the classroom, *Pediatric Obesity*, 13, 614– 620

[7] Castelnovo, A., Crupi, R., Greco, G. *et al.* A clarification of the nuances in the fairness metrics landscape. *Sci Rep* 12, 4209 (2022).

[8] Sapiezynski, P., Stopczynski, A., Lassen, D.D. *et al.* Interaction data from the Copenhagen Networks Study. *Sci Data* 6, 315 (2019).

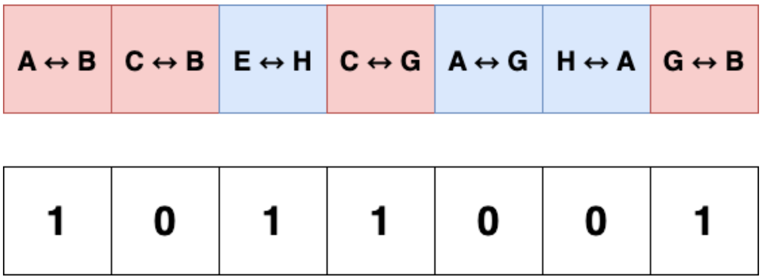

Figure 1: Starting from a vector of edges to be removed (in red) or added (in blue), the algorithm creates binary chromosomes to find the solution. Every "1" results in a modification to the original network structure. Conversely, each "0" implies no modification will concern the corresponding edge.

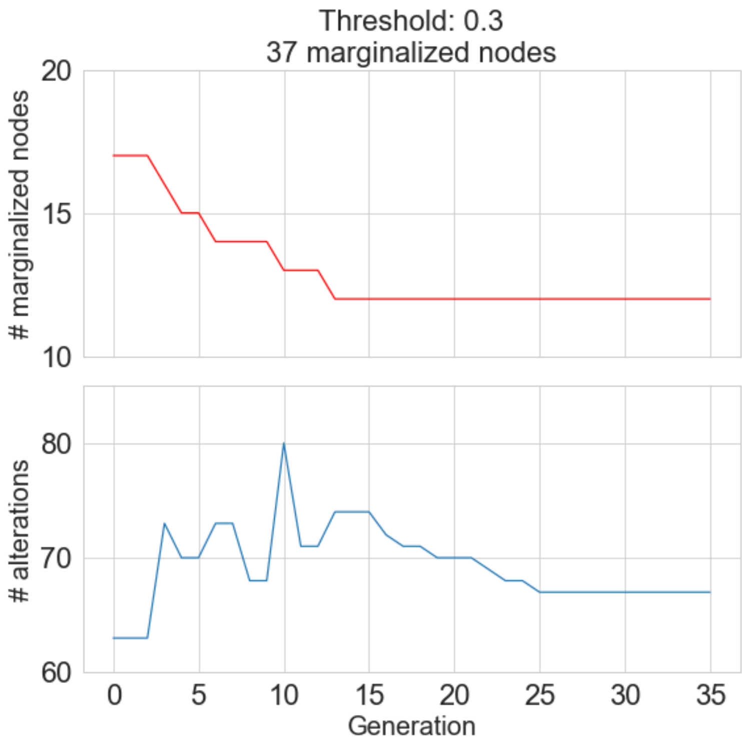

Figure 2: Results on the Copenhagen dataset with a global addition strategy. Of the 37 marginalized nodes detected with a threshold of 0.3, only 12 are left after 25 generations and 67 added edges.