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The Effect of Homophily on Disparate Visibility of Minorities in People Recommender Systems

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Abstract

Evaluating (and mitigating) the potential negative effects of algorithms has become a central issue in computer science. While research on algorithmic bias in ranking systems has dealt with disparate exposure of products or individuals, less attention has been devoted to the analysis of the disparate exposure of subgroups of online users.

In this paper, we investigate the visibility of minorities in people recommender systems in social networks. Specifically, we consider a bi-populated social network, i.e., a graph where the nodes belong to two different groups (majority and minority) and, by applying state-of-the-art people recommenders, we analyze how disparate visibility can be amplified or mitigated by different levels of homophily within each subgroup.

We start our analysis on real-world social graphs, where the two subgroups are defined by sensitive demographic attributes such as gender or age. Our findings suggest that the way and the extent to which people recommenders can produce disparate visibility on the two subgroups, might depend in large part on the level of homophily within the subgroups. To verify these findings, we move our analysis to synthetic datasets, where we can control characteristics of the input social graph, such as the size of the minority and the level of homophily. Our results show that homophily plays a key role in promoting or reducing visibility for different subgroups under various combinations of dataset characteristics and recommendation algorithms.

1 Introduction

People recommender systems, also known as contact recommenders or *who-to-follow* link recommenders (Guy and Pizzato 2016; Sanz-Cruzado and Castells 2018a), suggest to users possibly relevant new connections. These algorithms are a core functionality of every social media platform, as they contribute to stimulate new interactions, ultimately affecting the growth of the network (Su, Sharma, and Goel 2016). As such, they can play a key role in building the "social capital" of individuals (e.g., their number of followers). Besides general-purpose social networking platforms, people recommenders are also widely used to suggest connections between users in other environments, such as employment services (Heap et al. 2014; Liu et al. 2016b; 2016a; Ha-Thuc et al. 2016; Domeniconi et al. 2016), educational services (Vassileva, McCalla, and Greer 2016; Zhang et al. 2016), co-workers suggesting (Guy, Ronen, and Wilcox 2009) or expert finding (Hsu, Li, and Tseng 2016; Spaeth and Desmarais 2013; Guy et al. 2013).

It is thus of great importance to study potential algorithmic bias that might lead to disparate visibility of individuals. For instance, Su, Sharma, and Goel (2016) analyzed the abrupt changes in Twitter's network structure after the introduction of the "Who to Follow" feature, and found that users across the popularity spectrum benefitted from the recommendations; however, the most popular users profited substantially more than the average. Similar findings were reported by Daly, Geyer, and Millen (2010), who conducted a large-scale user study on IBM's Social-Blue social network site. While these two works focus on the inequalities at the level of individual users, some authors have analysed a *glass ceiling*[1] effect for women in social networks (Nilizadeh et al. 2016). For instance, Stoica, Riederer, and Chaintreau (2018) investigate the role of gender in organic and artificial growth of social networks, using a large social graph from Instagram, where women are the majority. Their theoretical model predicts a glass ceiling at the expense of a minority, but their empirical observations show a glass ceiling effect against the female majority. They explain this apparent contradiction by the different level of homophily of the two groups.

In this paper, *we provide a systematic analysis of the effect of homophily on disparate visibility of minorities in people recommender systems*. Homophily, the tendency of people to connect with others who are similar to them, is one of the main driving forces behind the organic growth of a social network, thus strongly influencing the main input of people recommender systems, i.e., the structure of the network. The next toy example shows the potential effect of homophily on the recommendations provided by an algorithm.

Example. Figure 1 depicts two social networks. In both cases, initially (left) each social graph has ten nodes: 7 in the majority group (blue), and 3 in the minority group (red).

[1]This is a metaphor referring to a sort of invisible barrier that prevents a group of people from rising in a hierarchy.

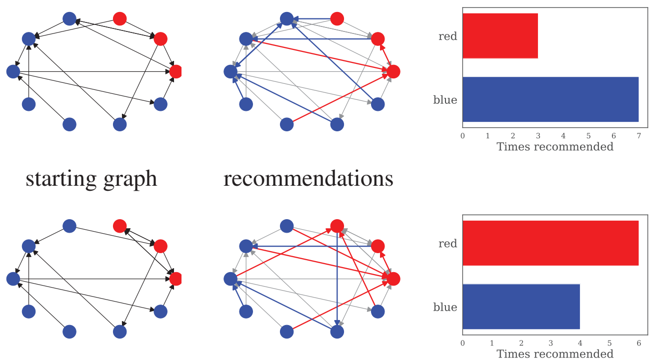


Figure 1: (Best seen in color.) Example depicting the role of homophily in a recommender system. Two social networks (top and bottom) are composed of ten nodes: 7 in the majority group (blue), and 3 in the minority group (red). The graphs are directed: a link (u, v) indicates the fact that u *follows* v. The graphs in the center reports the links recommended using the color of the node which is recommended.

However, in the bottom case the minority exhibits a stronger level of homophily: users belonging to the minority (red) group tend to connect among themselves more than the ones in the network on the top case (a more formal definition of homophily will be given in Section 3). We assume a "preferential attachment" recommender, which suggests to connect to the node with the highest number of followers from the set of nodes at distance 2, i.e., nodes followed by her neighbors. The graphs in the center column depict the recommendations produced, where the color of an edge is the same as that of the node who gets recommended to a source user. It is evident that homophily allows minorities to get much more visibility with respect to a less homopilic scenario (i.e., in the bottom network of the mid column, the number of red edges has increased with respect to the one above it, while that of the blue nodes has decreased).

Paper contributions and roadmap. In this paper, we characterize the visibility given by different recommendation algorithms to different groups of users, as a function of their relative *sizes* and the *homophily* of each group. We perform experiments with both real-world social networks, with groups defined by sensitive features such as gender or age, and synthetic graphs where we can explore different combinations of majority/minority sizes and homophily. This study sheds light into phenomena that suggest we must measure and mitigate negative effects of recommender systems, including user discrimination and unfairness (Ekstrand, Burke, and Diaz 2019) and a network's possible lack of resilience (García, Mavrodiev, and Schweitzer 2013). Specifically, our paper makes the following contributions:

- We provide a systematic study of the disparate visibility produced by contact recommendation algorithms, on real social networks and on synthetic datasets;
- We show that homophily plays a key role in the visibility given to different groups; when the minority is homophilic, there is a disparate visibility in favor of the minority class; when the minority is not homophilic, the disparate visibility is in favor of the majority class;
- Consistently with the literature, our analysis shows that recommenders amplify the rich-get-richer phenomena, thus introducing inequality of visibility. Such observed inequality, however, is stronger within the minority class compared to the majority class, especially when the minority is homophilic. This is explained by the fact that the minority class is over-represented in the sub-population of most recommended nodes when the minority is homophilic, and under-represented when the minority is not homophilic;
- We show that, when taking into account the initial in-degree, nodes in the minority class are disadvantaged in terms of visibility, regardless of the homophily of the minority class. In other words, among nodes with similar in-degree, the ones that belong to the majority class are likely to be recommended more;
- Finally, we show that the relative size of the minority does not impact visibility as much as homophily does.

The rest of the paper is structured as follows. Section 2 discusses related work. Section 3 introduces the metrics and algorithms we consider. Section 4 presents the experiments performed on real graphs and Section 5 those on synthetic graphs. Finally, Section 6 presents our conclusions.

2 Related Work

Su, Sharma, and Goel (2016) analyze a large-scale proprietary dataset containing a complete snapshot of Twitter and its "Who-To-Follow" recommender. Specifically, they study user behavior before and after the introduction of the recommender system in this social platform. They found a faster in-link growth for popular nodes, with a sub-linear popularity effect. In contrast with our work, user demographics were not taken into account and consequently, the role of homophily was not considered. We also consider more than one algorithm and measure the effect of the recommender at both the individual and the group level. Our study suggests that node popularity (in our case, represented by in-degree) is not the only crucial factor needed to characterize the rich-the-richer phenomenon, since popular nodes are treated differently according to the group they belong to (i.e., majority or minority) and the level of homophily in a group.

Daly, Geyer, and Millen (2010) investigated how recommendations can affect the global and local structure of a network. They focused on differences in topological features such as degree distribution skewness and node betweenness. In contrast, in our study we consider more properties of the nodes (such as the group they belong to and the visibility they obtain), in addition to characteristics such as node degree that have been previously studied.

Nilizadeh et al. (2016) were able to prove a *glass ceiling* effect in social networks. They investigated how perceived gender and online visibility can be linked, showing that users perceived as female experience a "glass ceiling" effect, similar to the one that makes it harder for women to reach higher positions in companies. This study was a seminal work around discrimination in social media interactions, which exaggerates stereotypes present in society. Our work tries to go in-depth into this phenomenon, trying to understand how network interactions along with recommendation algorithms might lead to disparate visibility of minority groups (e.g., how homophily affects the generated recommendations).

Lee et al. (2019) analyzed the characteristics of minorities of different sizes in a bi-populated graph, introducing homophily in a network growth process. We extend the model they proposed to analyze recommendation algorithms on synthetic data.

Karimi et al. (2018) studied disparate effects introduced by homophily, such as disparities in ranking distribution over subgroups, but without investigating its consequences on recommendations. This work strongly motivates ours, showing the research gap related to recommender systems effects.

In recent work, Stoica, Riederer, and Chaintreau (2018) investigate the role of gender in organic and artificial growth of social networks, using a large social graph from Instagram, where female are the majority class. Their theoretical model predicts a glass ceiling at the expense of a minority, but their empirical observations show glass ceiling against the female majority. They reconcile this apparent contradiction by extending their theoretical model to keep in consideration the different level of homophily of the two groups: in particular, a homophilic minority can flip the glass ceiling effect at the expense of the majority. Our systematic analysis confirms this intuition.

Related to our findings is also the *few-get-richer effect* phenomenon, which explains how the minority class tends to be top-ranked by popularity-based systems. This phenomenon has been analytically proven by a recent work by Germano, Gómez, and Mens (2019) and, although not embedded in the algorithms we considered, it finds empirical evidence in our experiments.

3 Preliminaries

We consider a bi-populated and directed social network, represented as a graph $G = (V, E, c)$ where V is the set of nodes, $E \subseteq V \times V$ is the set of directed edges, such that an edge $(u, v) \in E$ indicates the fact that u *follows* v, and $c : V \to \{V_1, V_2\}$ is a function assigning each node to one of two classes V_1, V_2 which partition V. We denote by s_1 the fraction of nodes belonging to the first class (i.e., $s_1 = |V_1|/|V|$) and by s_2 the fraction of nodes belonging to the second class (i.e., $s_2 = 1 - s_1$).

We also consider a people recommender system represented by a function $\ell : (V \times V) \setminus E \to [0, 1]$, which associates to each non-existing edge (u, v) a score $\ell(u, v) \in [0, 1]$. From a probabilistic standpoint, $\ell(u, v)$ can be interpreted as the probability for such recommendation to create a new connection that is accepted by u. In each round of recommendation, the system recommends to each node $u \in V$ a set $R(u)$ of other nodes to follow, where $|R(u)| = k$, for a given parameter $k \in \mathbb{N}^+$. Typically, $R(u)$ will contain top-k nodes v having the largest values of $\ell(u, v)$.

Visibility. In this work, we consider one single round of recommendation and focus on how many times each node v appears in the recommendation sets of all the other nodes. We call this quantity the *visibility* of v and denote it by

$$\psi(v) = |\{u \in V | v \in R(u)\}|.$$

In particular, we are interested in the fraction of recommendations that each of the two classes of nodes, V_1 and V_2, receives. The visibility of a specific subgroup i can be expressed as:

$$\mathcal{V}_i = \frac{1}{k|V|} \sum_{v \in V_i} \psi(v) \tag{1}$$

Disparate visibility. Considering the size of the two groups inside the graph, we can also refer to them as minority m and majority M, which respectively present relative size s_m and s_M. Then, the simplest way for defining differences in visibility between those two groups of users, used in ranking systems (Singh and Joachims 2018), is overall visibility normalized by group size, namely:

$$\Delta(\mathcal{V}) = \frac{\mathcal{V}_m}{s_m} - \frac{\mathcal{V}_M}{s_M} \tag{2}$$

We call this measure *disparate visibility*: this measure ranges in $[-\frac{1}{s_M}, \frac{1}{s_m}]$ and it is zero when the visibility (fraction of recommendations) received by the minority is equal to the relative size of the minority. Therefore, a disparate visibility close to zero represents a situation in which no group is favored, large negative values indicate the minority class is given a disproportionately large visibility, and large positive values indicate the majority class is given a disproportionately large visibility.

Homophily. Homophily is a well-known phenomenon in network science and can be expressed as *the tendency of people to connect to similar people*, or in our case, of people in a group to connect to people in the same group. We measure homophily with respect to a random configuration, inspired by work analyzing dyadicity in signed networks (Park and Barabási 2007):

$$h_i = \frac{|E_{ii}|}{|E_{i.}|} - s_i \tag{3}$$

where $E_{ii} = \{(u, v) \in E | u \in V_i \wedge v \in V_i\}$ and $E_{i.} = \{(u, v) \in E | u \in V_i\}$. This measure expresses the difference between the number of observed intra-group edges and the expected number if edges were created at random. It ranges in the interval $(-s_i, 1 - s_i]$. A group is called homophilic if the tendency to connect to nodes of the same group is stronger than expected ($h_i > 0$), heterophilic when this tendency is weaker than expected ($h_i < 0$), and neutral if the number of edges towards each group is consistent with the proportion of nodes in each group ($h_i = 0$).

Recommendation algorithms. We consider four different methods for link recommendation and investigate the node visibility generated by those. One is a baseline random recommender, and the other three are state-of-the-art algorithms, representative of three distinct families of methods (based on topology, random walks, and collaborative filtering), that we have chosen because of their popularity and performance (Li, Fang, and Sheng 2017; Sanz-Cruzado and Castells 2018b).

ADA: Network Topology Based. Among the different heuristics which aim to define similarity between nodes looking at the graph topology, we select the *Adamic-Adar coefficient* (for short "ADA" in the rest of the paper), method that penalizes connections with high degree nodes.

SLS: Random Walks Based. As representative of random-walks based approaches, we use SALSA (Stochastic Approach for Link-Structure Analysis) ("SLS" in the rest of the paper), which is at the basis of the *who-to-follow* recommender at Twitter (Su, Sharma, and Goel 2016). Recommendation of a generic link is defined as the probability of the source node to jump to the target one, rather than to any other node in the graph.

ALS: Collaborative Filtering Based. Connections among nodes can be considered as implicit feedback in a collaborative filtering approach. An Alternating Least Squares algorithm ("ALS" in the rest of the paper) is selected to perform recommendations (Hu, Koren, and Volinsky 2008). New links are suggested based on latent features extracted from the adjacency matrix.

RND: Random baseline. As baseline, we consider a random recommender ("RND" in the rest of the paper), which picks recommendations uniformly at random from the candidate nodes at distance 2.

Aligned with the common practice among social network providers, such as Facebook[2] and Twitter[3], which suggest users with mutual connections, recommendations in our experiments are chosen from the set of missing links at distance two (friends of friends).

4 Observations on Real-World Graphs

In this section, we analyze data from two social networking sites, exploring how the role of homophily on groups of nodes can play a role in the generation of recommendations. We remark that this experimentation is made difficult because there are very few social networking datasets where nodes can be partitioned into classes based on demographic attributes.

4.1 Datasets

TUENTI. Known as the "Spanish Facebook," Tuenti has been a popular social networking site in Spain.

The data we use includes some demographic information about users (Laniado et al. 2016).

Nodes are users and edges are defined by wall-post interactions, i.e., a user posting on another user's "wall." Specifically, a directed edge (u, v) exists if user u posted at least t times on the wall of a user v. To remove sporadic interactions, we consider $t = 3$ as a threshold. This network has 8,983,560 nodes (users) and 17,830,103 edges.

In order to have a fair comparison of the performance with different datasets, we decided to create samples of equal size. Finally, the sample size was set to 500,000 nodes, for computational reasons and due to the large amount of experiments we performed. To sample, we follow the work by Wagner et al. (2017) and use a random walk based algorithm, which has been shown to preserve characteristics that are of interest in our analysis, such as the relative sizes of minority and majority classes, as well as their level of homophily. The resulting network contains 500,000 nodes and 2,813,744 edges.

Next, we create different bi-populated networks using different partitions by gender and age, whose basic characteristics are reported in Table 1 and Figure 2 (in the table and figure, datasets are ordered by decreasing homophily of the minority):

- **TUENTI-G** is the network partitioned by gender. It is characterized by an absence of homophily in both groups and, among the three partitions of the original dataset, it is the one with the largest minority class (females, $s_m = 0.39$).
- **TUENTI-A16** is the network partitioned by age with 16 as cut-off. This dataset presents two groups which are both homophilic, with a smaller minority than the previous case (younger than 16, $s_m = 0.30$).
- **TUENTI-A30** is also based on a partition by age with 30 as cut-off. It presents a very small minority (older than 30, $s_m = 0.04$) and it lacks homophily in both groups.

POKEC. This is a popular social networking site in Slovakia. Anonymized data is publicly available,[4] and includes some demographic information.

In total, the network contains 1,632,640 nodes (users) and 22,301,602 edges, where each edge represents a "follow" relationship, which can be non-symmetrical. We adopt the same sampling approach used for Tuenti and produce a network containing 500,000 nodes and 8,635,662 edges.

We create the two classes of nodes by partitioning by age with a cut-off of 21. The resulting dataset, dubbed **POKEC-A21**, presents quite well-balanced groups (minority is younger than 21, $s_m = 0.46$), with the minority more homophilic than the majority.

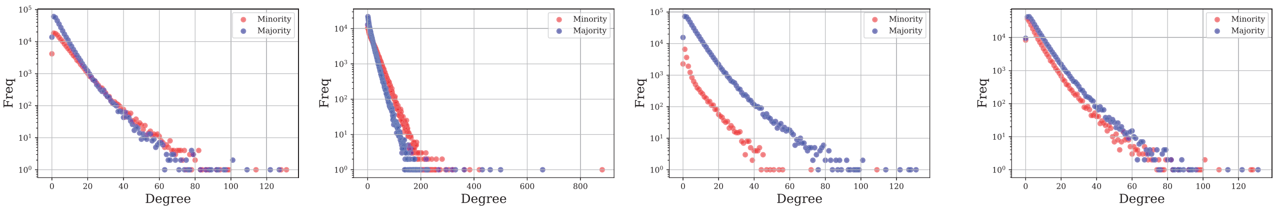
Name	Attribute	$\lvert V\rvert$	$\lvert E\rvert$	s_m	h_m	h_M
TUENTI-A16	age	500000	2813744	0.30	0.42	0.14
POKEC-A21	age	500000	8635662	0.46	0.34	0.19
TUENTI-A30	age	500000	2813744	0.04	0.08	0.02
TUENTI-G	gender	500000	2813744	0.39	0.02	0.07

Table 1: Characteristics of real-world social networks analyzed: dataset name, attribute used for partitioning, number of nodes, number of edges, proportion of the minority size, homophily of the minority, and homophily of the majority.

[2]https://www.facebook.com/help/163810437015615

[3]https://help.twitter.com/en/using-twitter/account-suggestions

[4]https://snap.stanford.edu/data/soc-Pokec.html



(a) TUENTI-A16 (b) POKEC-A21 (c) TUENTI-A30 (d) TUENTI-G

Figure 2: In-degree (number of followers) distribution of the minority and majority classes in each social network. We can observe that in the datasets with a homophilic minoritiy (TUENTI-A16 and POKEC-A21), the minority class exhibits an advantage in terms of high in-degree nodes.

Network	Method	$\Delta(\mathcal{V})$	$\Delta(\mathcal{V}_{<q_{90}})$	$\Delta(\mathcal{V}_{<q_{80}})$	$\Delta(\mathcal{V}_{>q_{90}})$	$\Delta(\mathcal{V}_{>q_{80}})$
TUENTI-A16 $s_m = 0.3$ $h_m = 0.42$	ALS	0.517	0.184	0.086	0.681	0.630
	SLS	0.264	0.069	0.014	0.464	0.396
	ADA	0.134	0.071	0.048	0.249	0.209
	RND	0.149	0.155	0.154	0.119	0.123
POKEC-A21 $s_m = 0.46$ $h_m = 0.34$	ALS	0.900	0.645	0.401	0.985	0.944
	SLS	0.571	0.312	0.196	0.731	0.653
	ADA	0.328	0.259	0.208	0.434	0.386
	RND	0.310	0.322	0.309	0.285	0.282
TUENTI-A30 $s_m = 0.04$ $h_m = 0.08$	ALS	-0.276	-0.397	-0.433	-0.224	-0.306
	SLS	-0.350	-0.446	-0.504	-0.251	-0.328
	ADA	-0.359	-0.436	-0.501	-0.200	-0.273
	RND	-0.333	-0.423	-0.503	-0.105	-0.197
TUENTI-G $s_m = 0.39$ $h_m = 0.02$	ALS	-0.264	-0.323	-0.292	-0.267	-0.178
	SLS	-0.291	-0.348	-0.324	-0.261	-0.200
	ADA	-0.212	-0.252	-0.235	-0.157	-0.122
	RND	-0.149	-0.186	-0.168	-0.086	-0.062

Table 2: Disparate visibility ($\Delta(\mathcal{V})$ introduced by different recommenders: $\Delta(\mathcal{V}_{<q_{90}})$ and $\Delta(\mathcal{V}_{<q_{80}})$ refers to the same measure when removing the top-10% and top-20% of in-degree nodes, respectively, from each class; while $\Delta(\mathcal{V}_{>q_{80}})$ and $\Delta(\mathcal{V}_{>q_{90}})$ refers to the measure computed on the top-20% and top-10% in-degree nodes of each class.

Figure 2 reports the in-degree (number of followers) distribution of the minority and majority classes in each social network. We can observe that in the datasets with a homophilic minoritiy (TUENTI-A16 and POKEC-A21), the minority class exhibits an advantage in terms of high in-degree nodes.

4.2 Disparate visibility

We next apply the four link recommendation methods to all our networks, recommending to each node $k = 5$ other nodes; then we measure visibility, i.e., how many times each node appears in the recommendations to other nodes. Table 2 reports disparate visibility $\Delta(\mathcal{V})$ between the minority and majority class, defined as in Eq. 2: a value of $\Delta(\mathcal{V}) > 0$ indicates that the minority class is favored in terms of visibility, while $\Delta(\mathcal{V}) < 0$ indicates that the majority class is favored. A first observation we can draw is the following:

Observation 1 *In graphs with a homophilic minority, there is a disparate visibility in favor of the minority class. When the minority is not homophilic, the disparate visibility is in favor of the majority class. This holds for all the link recommendation methods we tested.*

Although the observation above holds true regardless of the recommender we tested, we observe that the effect is more evident with the two more sophisticated methods, ALS and SLS. For instance, in the POKEC-A21 dataset, with a minority almost as large as the majority ($s_m = 0.46$), a homophilic minority ($h_m = 0.34$) and a slightly homophilic majority ($h_M = 0.19$), the ALS recommender gives high visibility to the minority ($\Delta(\mathcal{V}) = 0.9$).

We conjecture that this result might depend on the fact that, when in presence of a homophilic minority, the minority class presents more nodes with high in-degree than the majority. Thus Table 2 also reports what happens when we exclude the top-20% (column $\Delta(\mathcal{V}_{<q_{80}})$) and the top-10% (column $\Delta(\mathcal{V}_{<q_{90}})$) high in-degree nodes from each of the two classes.

As expected, when we remove hubs from the analysis, the disparate visibility in favor of the minority class in the datasets with homophilic minority (TUENTI-A16 and POKEC-A21) gets reduced substantially. This is confirmed by the columns $\Delta(\mathcal{V}_{>q_{80}})$ and $\Delta(\mathcal{V}_{>q_{90}})$ which focus only on the top-20% and the top-10% high-degree nodes, for which the disparate visibility in favor of the minority is very high. Of course this does not hold for the RND recommender, which depends much less on the in-degree of the nodes than the other recommenders.

When considering the TUENTI-G network partitioned by gender, the size of the minority is much smaller than that of the majority ($s_m = 0.39$), and both groups are characterized by neutral homophily (neither homophily nor heterophily). Under this setting, the distribution of visibility harms the minority. For nodes with highest degree, the effect is mitigated, but still indicating that minority nodes are receiving slightly less visibility than what should correspond to them given their degree. Consequently, excluding nodes with highest degree, the difference in visibility is even stronger, showing that minority long-tail nodes are at a disadvantage when compared to their peers in the other group.

TUENTI-A30 is characterized by the smallest minority ($s_m = 0.04$), and absence of homophily in both majority and minority groups. Under this setting, similarly to what happened in the TUENTI-G network, the minority receives less visibility (even more than in the TUENTI-G network). Also in this case, the effect is slightly mitigated when looking at the nodes in the top of the in-degree distributions and exaggerated for the rest of the graph.

Observation 2 *The hubs existing in the minority group receive large visibility. In contexts in which the minority is homophilic, this exaggerates the disparate visibility in favor of the minority. In contexts in which the minority is not homophilic, this helps slightly mitigate the disparate visibility against the minority.*

This last consideration motivates further investigation of the interplay between in-degree, visibility, and the belonging to the minority or the majority class.

4.3 Rich-get-richer effect

We next study inequality of visibility of nodes within each of the two classes. Figure 3 reports Lorenz Curves[5] of visibility of nodes (ψ) and in-degree (denoted as d_{in}) inside the two subgroups. Lorenz Curves are a popular graphical tool to show the cumulative distribution of a variable inside a population, emphasizing the differences with respect to a hypothetical random distribution. They are widely used to evidence inequality in wealth distribution among countries or more generally, comparing the wealth distribution of subpopulations (Chakravarty 2012). These plots present on the x-axis the percentile of the population and on the y-axis the fraction of cumulative distribution of the wealth. For instance a point (0.8, 0.2) indicates that 80% of the population has 20% of the wealth. In case of absolute inequality, all the wealth is assigned to only one person and the line correspond to the x-axis. In the case of perfect equality, the wealth is distributed equally along the sample, corresponding to the $x = y$ diagonal.

In Figure 3, the "wealth" corresponds to the in-degree (denoted as d_{in}) of nodes and to their visibility (ψ) with respect to the recommendations produced by the ALS and SLS methods inside the two classes. We report only two methods for sake of space, the other methods produce similar results.

The first (well-known) observation on Figure 3 is that link recommenders amplify the intrinsic "inequality" of the in-degree distribution, as shown by the difference existing between the solid lines and the dashed lines. This rich-get-richer effect is innate in the link recommendation task, thus not surprising. Instead, more surprising is the fact that such effect is stronger within the minority than within the majority class (difference between the dashed blue line and the dashed red line) and this is consistent among all datasets and all recommenders, although being more evident in datasets with a homophilic minority. This confirms what we observed in Table 2, i.e., the fact that there are a few hubs that receive most of the visibility in the minority class.

Observation 3 *Recommenders amplify the rich-get-richer phenomena observed for in-degree, thus introducing more inequality of visibility. Such observed inequality is stronger within the minority class compared to the majority class, especially when the minority is homophilic.*

4.4 Most visible nodes

We investigate further these observations by showing the fraction of nodes of the minority class that belong to the most visible nodes. Figure 4 reports the fraction of nodes belonging to the minority class that are among the most visible ones on each dataset and for each recommender. For instance, in the left-most point of Figure 4(b) we can see that in the POKEC-A21 dataset, while the minority class represents 46% of the population, it rises to 58-65% (depending on the recommender) when checking only the 10% of most visible nodes. A similar observation holds for the other graph with homophilic minority (TUENTI-A16).

However, on graphs in which the minority is not homophilic, the trend is completely overturned. For instance, in the TUENTI-G dataset (Figure 4(d)) while the minority class represents 39% of the overall population, when focusing only on the sub-population of the 10% most visible

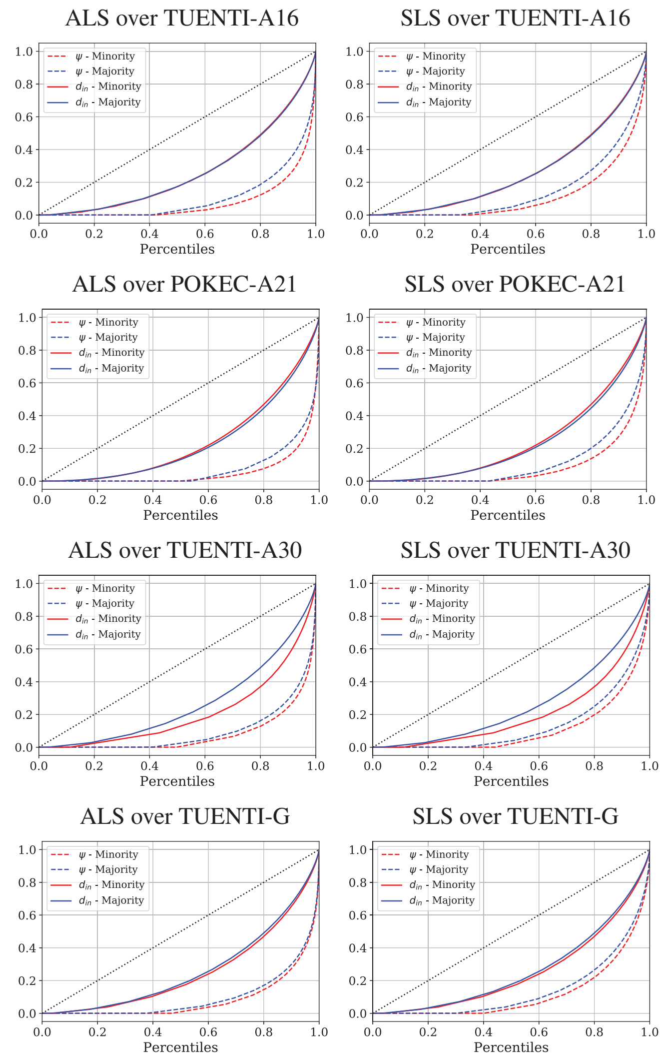


Figure 3: (Best seen in color.) Lorenz Curves depicting inequality. Dashed lines represent recommendations, solid lines represent in-degree. The minority is in red, the majority in blue. Recommendations introduce more inequality than the degree distribution, and this inequality is stronger in the minority class.

[5] https://en.wikipedia.org/wiki/Lorenz_curve

nodes, the minority class is under-represented: i.e., 32-37% (depending on the recommender).

Observation 4 *The minority class is over-represented in the sub-population of most recommended nodes when the minority is homophilic, and under-represented when the minority is not homophilic.*

Most of these observations seen so far are rooted in the fact that in the datasets with a homophilic minority (TUENTI-A16 and POKEC-A21), in-degree influences differences in visibility distribution.

However, it is interesting to ask whether two nodes with similar in-degree, one from the minority and one from the majority class, have similar visibility.

4.5 Individual fairness

We now adopt an individual fairness standpoint, i.e., the principle according to which similar individuals should receive a similar treatment (Dwork et al. 2012). In our setting, being similar means having similar in-degree (e.g., a similar number of "followers" in a social networking site). Therefore, we sort nodes by ψ/d_{in}, i.e., the number of times a node is recommended divided by its in-degree.

Figure 5 shows that, contrarily to what is seen in Figure 4, if we normalize by in-degree then nodes in the minority group are under-represented among top nodes, regardless of the level of homophily of the minority. For instance, in all graphs and all recommenders, if we take the top-40% nodes by ψ/d_{in}, then the fraction of nodes belonging to the minority class is always below the dotted line, which represents the relative size of the minority in the network.

Observation 5 *When taking into account in-degree, nodes in the minority class are disadvantaged in terms of visibility, regardless of the homophily of the minority class. In other words, among nodes with similar in-degree, the ones that belong to the majority class are likely to be recommended more.*

5 Observations on Synthetic Graphs

Synthetic networks allow us to test the extent to which the observations on real-world graphs hold for a wider range of configurations: in particular, they allow us to control the level of homophily in the two groups and the relative size of the minority (which would be impossible to do on real-world graphs).

We next discuss how we generate syntectic networks.

5.1 Data generation process

Our goal is to generate bi-populated directed networks where we can control the homophily of each of the two groups and their relative size. This is a non-trivial task. Our solution is inspired by the *Biased Preferential-Attachment* model introduced for undirected graphs (Lee et al. 2019), and that we extend to produce directed graphs.

Under our model, the tendency to connect to other nodes is regulated by in-degree distribution and *in-process homophily*. The latter, which represents for each group the tendency to connect to same peers along the process, is indicated by ρ, which is a non-negative coefficient bounded in the interval $(0, 1]$. Nodes are partitioned into a minority m and a majority M, where a generic node v is associated to the minority m with probability p_m and to the majority M with probability $p_M = (1 - p_m)$. In the long run, these two probabilities correspond to the fraction of nodes belonging to the two partitions. The value of ρ depends on the class of the source node, i.e., assuming u as new node to add with $c(u) = m$, ρ_{uv} corresponds to h_m if $c(u) = c(v)$, otherwise $\rho_{uv} = (1-h_m)$. Considering the in-process homophily values for the minority and the majority group, respectively expressed as ρ_m and ρ_M, these two parameters are directly proportional to the observed homophily indicated as h_m and h_M. In general, fixing $\rho = 0.5$ for one class generates a neutral group ($h = 0$), $\rho > 0.5$ generates a homophilic group ($h > 0$) and, finally, $\rho < 0.5$ generates a heterophilic group ($h < 0$). The process designed to generate a bi-populated graph $G = (V, E, c)$ is the following:

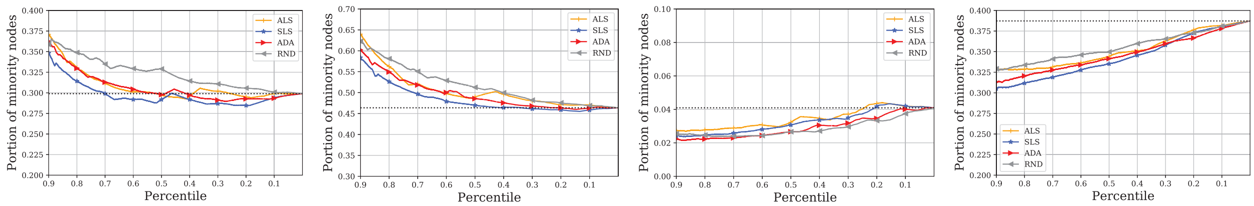
1. **Initialization.** $|V| = N$ is the network size and d_{out} the number of outgoing out-links from each new node (i.e., $|E| = N \times d_{out}$). Then d_{out} nodes are initialized, forming a fully-connected graph. To reduce randomness, in the initialization phase there is no real majority class, since the two groups are equally distributed.
2. **Add node.** A new node v is added to the graph, belonging to the minority with probability p_m.
3. **Add edges.** For the new node v, we generate d_{out} out-links, each one with the following probability that incorporates both in-process homophily and rich-get-richer effect:
$$p_u = \frac{\rho_{vu}\big(d^{in}(u) + A\big)}{\sum_{w \in V} \rho_{vw}\big(d^{in}(w) + A\big)}$$
The A constant, introduced in the original Biased Preferential-Attachment model to avoid penalizing new nodes, is fixed to 1.

The process terminates when the graph reaches $|V| = N$.

5.2 Impact of homophily

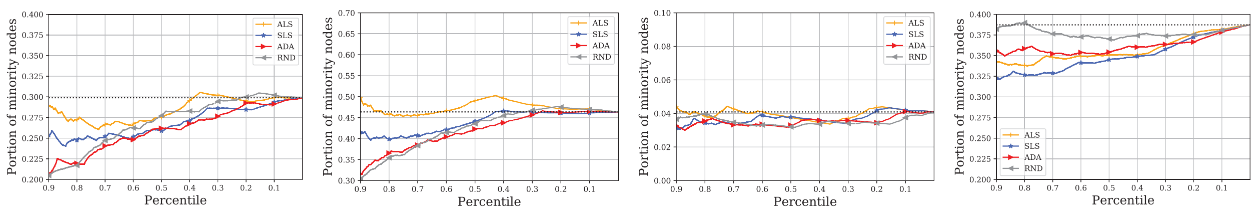
In this first set of experiments, we aim at investigating homophilic and heterophilic situations for both groups. We keep the same minority/majority partition ($s_m = 0.3$) with networks having 10,000 nodes each and, to show more robust results, each configuration expressed in terms of (ρ_m, ρ_M), is tested 10 times. Consequently, metrics computed over networks with the same configuration are evaluated through their average. We generate three distinct groups of configurations:

- **S1.** We create a neutral majority with $\rho_M = 0.5$, and vary the level of homophily of the minority $\rho_m \in [0.2, 0.9]$.
- **S2.** We create a neutral minority with $\rho_m = 0.5$, and vary the level of homophily of the majority $\rho_M \in [0.2, 0.9]$.
- **S3.** We create a homophilic majority and a homophilic minority, testing 4 possible configurations of (ρ_M, ρ_m) in the set $\{0.7, 0.9\}$.



(a) TUENTI-A16 (b) POKEC-A21 (c) TUENTI-A30 (d) TUENTI-G

Figure 4: Portion of the minority class in the top nodes, sorted by ψ.



(a) TUENTI-A16 (b) POKEC-A21 (c) TUENTI-A30 (d) TUENTI-G

Figure 5: Portion of the minority class in the top nodes, sorted by ψ/d_{in}.

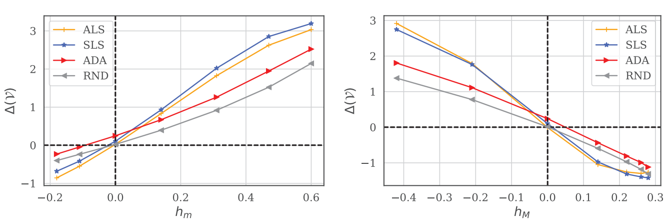


Figure 6: (Best seen in color.) Distribution of $\Delta(\mathcal{V})$ observed in S1 and S2. The minority comprises 30% of the nodes ($s_m = 0.3$). In the left plot, the majority is neutral and the heterophily/homophily of the minority varies. In the right plot, the minority is neutral and the heterophily/homophily of the majority varies.

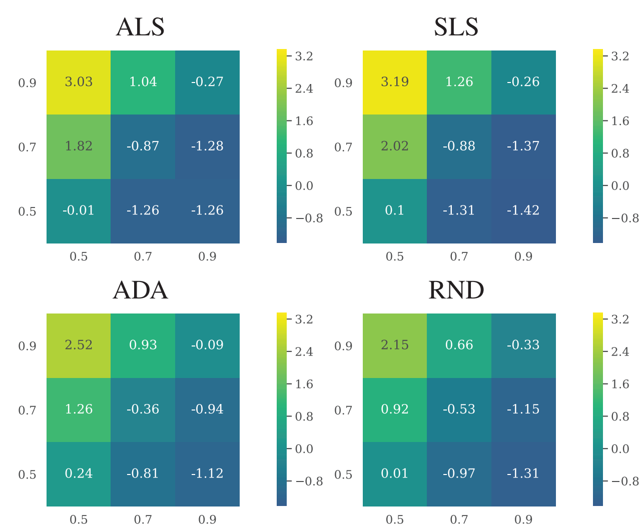


Figure 7: (Best seen in color.) Visibility $\Delta(\mathcal{V})$ computed over networks characterized by different homophily of the minority ρ_m (y-axis) and homophily of the majority ρ_M (x-axis).

Figure 6 presents the overall visibility, $\Delta(\mathcal{V})$, given by the different recommenders, comparing the two settings in which a group is homophilic but the other is not (S1 and S2). Looking at the $\Delta(\mathcal{V})$ obtained in configuration S1 (left side in Figure 6), the minority indeeds obtains more visibility when it is homophilic. In particular, the more the minority is homophilic, the more visibility it gets. In contrast, if the minority is heterophilic, it is the majority that benefits in terms of visibility. Although all the recommenders behave similarly, these effects are more evident in ALS and SLS. In S2, the homophilic majority leads to an analogous effect; indeed when homophilic, it receives more visibility, while when heterophilic, it facilitates the neutral minority to get more than their representation (right side of Figure 6).

The analysis of the overall visibility in the case in which both groups are homophilic (S3) is presented in the heatmap in Figure 7. The x-axis represents ρ_M, while the y-axis reports the ρ_m values; each cell of the matrix contains the values of $\Delta(\mathcal{V})$ under that setting. In case of neutral homophily for both groups ($\rho = 0.5$), no disparate visibility is given by any of the algorithms (except for ADA, who gives a slight advantage to the minority). For the scenario in which both groups are highly homophilic ($\rho = 0.9$ and $\rho = 0.7$), the majority is slightly advantaged. The worst scenarios can be observed in cases of one extremely homophilic class and neutral the other (top left and bottom right cells of each matrix), which present the values of $\Delta(\mathcal{V})$ with strongest intensity in absolute value (again, this phenomenon is especially emphasized by ALS and SLS). These extremes cases cap-

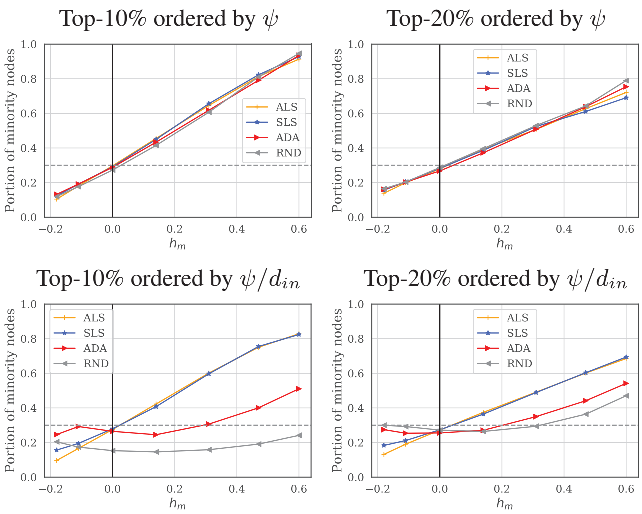


Figure 8: Fraction of minority class in S1 in the top positions of rankings ordered by visibility ψ (first row) and by degree-normalized visibility ψ/d_{in} (second row).

ture a trend in each heatmap in the figure, which indicates that as soon as a group increases its homophily, it increases its visibility.

To further confirm the role of homophily when considering visibility received at individual level, as previously investigated for real data, we focus on the ranking generated either by visibility ψ or by degree-normalized visibility ψ/d_{in}. We look at the fraction of nodes belonging to the homophilic class in the top-10% and top-20% of the most recommended nodes. Since we are capturing the "rich-get-richer" and "individual fairness" phenomena we previously captured for the minority group, in Figure 8 we report the results for S1. The first row of the figure shows that a stronger homophilic tendency leads to present the homophilic class in the highest positions of the recommendations, for all the algorithms. While, looking at the second row, where nodes are ordered by visibility normalised by the in-degree, the effect is mitigated. In particular, for ADA, the configuration with small homophily presents a minority still underrepresented.

5.3 Impact of minority size

Synthetic networks also enable us to investigate how visibility varies with the relative size of the minority in the graph. To do so, we generate a fourth group of configurations, **S4**. Keeping the minority homophilic ($\rho_m = 0.8$) and the majority neutral ($\rho_m = 0.5$), we range the minority size s_m from 5% to 45%. Each configuration in S4, characterized by a different s_m, corresponds to a graph with 10,000 nodes and is generated 10 times (again, the results we present are an average of those obtained for the 10 networks depicting the same configuration). The observed homophily (h_m) presents $\mu = 0.4$ and $\sigma^2 = 0.01$, showing that the data generation process is stable with respect to the different h_m.

In Figure 9, we report the $\Delta(\mathcal{V})$ obtained for each configuration. We observe that being a small minority ($s_m = 0.05$)

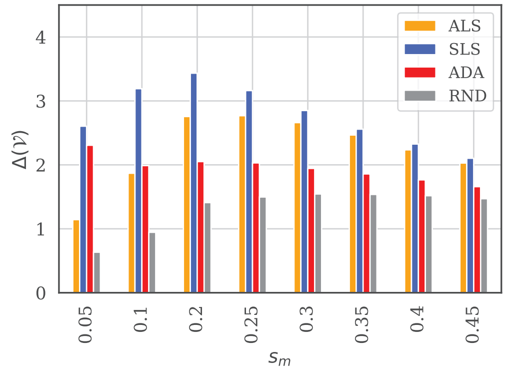


Figure 9: Distribution of $\Delta(\mathcal{V})$ for different minority sizes s_m and a homophilic minority ($\rho_m = 0.8$). The size of the minority does not have an effect on visibility as dramatic as the effect of homophily.

can mitigate the homophily effect, while keeping the minority with a size much lower than half of the graph ($s_m \in 0.1, 0.2, 0.25$) can positively impact the final gain in visibility. Despite these considerations, the size does not impact visibility as much as homophily, since $\Delta(\mathcal{V})$, for each recommender, ranges in a small interval.

Observation 6 *The relative size of the minority does not impact visibility as much as homophily does.*

6 Conclusions and Future Work

Although we have covered a wide range of scenarios in this work, we include in this section along with our conclusions several limitations and possible new directions.

The main take-home message of this work is that homophily plays a key role in the visibility that is given to a group, sometimes regardless to the fact that this group may be a minority in the network. We note that through the analysis we have done, we do not try to infer the reason behind the observed phenomena, since our findings are mainly driven by empirical evidence. This clearly leaves space to further investigate analytically how homophily leads to disparate visibility, and we expect this paper may initiate more work in that direction.

We highlight algorithmic biases expressed in terms of visibility, in a static "single round" of recommendations but saying nothing about the long-term effect of the algorithms. A natural extension would be a setting where the graph evolves dynamically and repeated recommendations are generated, opening to scenarios where homophily may change over time as well as with the partition of minority-majority.

The introduced visibility metric accounts for distribution of recommended users but does not provide any information regarding the ones receiving the suggestion. In this way, this metric tells nothing about which source a group benefited from, in terms of accumulated visibility. For this reason, we plan to extend the study, designing alternative visibility metrics, able to integrate this feature. In addition, this kind of analysis would clarify to what extent the effects are driven by in-degree.

The synthetic data generator we have used has been designed to reproduce user homophily and rich-get-richer effects, and the choice of using the biased preferential attachment is due to its proven capacity to reproduce quite well social network structures (Barabasi and Albert 1999). Nevertheless, this assumption may be too narrow, and a natural open question to address in the future would be the comparison of results produced by different data generation processes. Also, extending this analysis to other models will open to other use-cases where homophily would raise in other forms, such as job platforms interaction networks or research collaboration graphs.

Analogously, the experiments were designed assuming a sensitive attribute that allows us to split nodes only in two subgroups. In practice, user demographics may present more than two attribute values (e.g., age, education) and, in those cases, new definitions of disparate visibility and homophily are needed.

This work sheds light on some key ethical aspects to consider into the design of social networking products. Embracing these insights would lead to new mitigation strategies, able to control disparate visibility. We plan to develop in- and post-processing algorithms in this direction, evaluating them under various homophily and group fairness definitions.

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