Targeted Influence with Community and Gender-Aware Seeding

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ABSTRACT
When spreading information over social networks, seeding algorithms selecting users to start the dissemination play a crucial role. The majority of existing seeding algorithms focus solely on maximizing the total number of reached nodes, overlooking the issue of group fairness, in particular, gender imbalance. To tackle the challenge of maximizing information spread on certain target groups, e.g., females, we introduce the concept of the community and gender-aware potential of users. We first show that the network’s community structure is closely related to the gender distribution. Then, we propose an algorithm that leverages the information about community structure and its gender potential to iteratively modify a seed set such that the information spread on the target group meets the target ratio. Finally, we validate the algorithm by performing experiments on synthetic and real-world datasets. Our results show that the proposed seeding algorithm achieves not only the target ratio but also the highest information spread, compared to the state-of-the-art gender-aware seeding algorithm.

CCS CONCEPTS
• Theory of computation → Social networks; • Social and professional topics → Gender.

KEYWORDS
social networks, influence maximization, fairness

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1 INTRODUCTION
The influence maximization (IM) problem, which chooses a subset of users in the social network as seeds to maximize the number of influenced users [2, 3, 8, 11, 12, 14], has considerable applications, such as viral marketing, political campaigns, and so on. In [8], it has been proved that IM is NP-hard and a greedy algorithm can generate $(1 - \frac{1}{e})$-approximation solutions. However, traditional IM only focuses on the influence spread and neglects the disparity in underrepresented groups (URGs). For example, when the government wants to disseminate a piece of information about financial aid, a good seed group which maximizes the number of influenced individuals but does not take into account if struggling individuals learn about it, may not reach the population which needs it most.

Extensive research [5, 9, 19, 20, 24] has investigated numerous IM problem, which aim to provide fairness and deal with the disparity under various definitions, such as maximizing the influence on URGs while ensuring a minimum spread on the whole network [5], maximizing the minimum spread among all groups [24], balancing the numbers of seeds from different groups [19], and ensuring the ratios of influenced users in respective groups to be the same [9, 20]. Recently, the Disparity Influence Maximization (DIM) problem was proposed [22] to further focus on promoting URG to reach a target ratio, benefiting real-world applications with diverse needs. However, the Disparity Seeding algorithm [22] proposed to solve DIM is based on the ranking mechanism, neglecting the submodular property of IM and in turn resulting in a limited influence spread.

On the other hand, community-based approaches [4, 7, 10, 16, 18] have shown great strengths in solving IM in terms of both effectiveness and efficiency, since they can narrow down the possible seed candidates. Although the above approaches provide promising solutions to traditional IM, none of them has considered fairness. However, as indicated in previous studies [1, 20, 21], human social networks usually exhibit homophily, a tendency to favor interactions with similar individuals. For example, females are more likely to interact with females to form communities. Hence, an essential question is how to exploit such communities to improve seed selection so that a specified target gender ratio can be achieved. In this
paper, we use the relationships between communities and genders to design a community-based approach to solve DIM.

We start by analyzing a dataset from Facebook, where users have three modes of interactions, i.e., likes, comments, and tags. Based on these multi-type interactions, we apply a variant of the Leiden algorithm [23] to discover communities and classify them as male-dominant, female-dominant, and evenly-distributed communities depending on their majority gender. Our key findings are (a) the community structure is more crucial than the gender for the homophily phenomenon and (b) evenly-distributed communities are usually more influential than the other types of communities.

Leveraging the observations from our community analysis, we propose Community and Gender-Aware Seeding (CGaS) to improve various seeding approaches that are unaware of genders for solving DIM. CGaS introduces the swapping mechanism to refine the seed group so that the gender distribution of influenced users satisfies the target ratio specified by DIM. To evaluate the influence of a user on different genders, CGaS proposes a novel measure, the Gender-aware Potential Influence (GPI). Specifically, to gain more influenced users of the target gender, CGaS replaces the seeds having a small GPI on the target gender with users having a large GPI on the other gender while retaining the total influence spread. Note that CGaS offers great flexibility since it is applicable to refine the seed groups discovered by various seeding algorithms. Our experiments on the Facebook dataset demonstrate that CGaS can achieve the specified target gender ratio and outperforms Disparity Seeding [22] in terms of the influence spread. Our contributions include:

- We are the first to study the affinity between communities and genders in disparity influence maximization.
- We develop a novel community-gender aware seeding algorithm, CGaS which iteratively refines the seeds based on a new metric, the Gender-aware Potential Influence (GPI).
- The experimental results show that CGaS achieves more than two times the influence spread of Disparity Seeding on the Facebook dataset.

2 COMMUNITY ANALYSIS
2.1 Dataset and community detection
The dataset was gathered from voluntary senior students at 25 university departments through the Facebook API [22]. Specifically, the dataset contains 1,870 unique users (765 males and 1,105 females) and around 20 million interactions, each of which records users’ genders and the interaction type (i.e., likes, comments, or tags). The period of interactions spans from March 2008 to May 2016.

Following [13], we first discover communities by leveraging a variant of the Leiden algorithm [23], which is suitable for multi-type interaction social networks. Next, according to a third-majority known in politics [17], we define a community as a male-dominant (or female-dominant) community if the number of males (or females) is more than twice that of females (or males) in this community. Otherwise, it is an evenly-distributed community. As a result, we obtain 44 communities with an average size of 42.2 (±23.49) members, including 21 evenly-distributed (Even), 16 female-dominant (Female), and 7 male-dominant communities (Male).

Figure 1: Distributions of user interactions for tagging.

2.2 User interaction
We first examine the interaction pattern of users in different types of communities to study the effect of communities in terms of the type of communities their objects belong to. Due to the space limitation, we follow [22] to focus on the analysis of tags. Figure 1(a) shows the percentage of different types of communities that users in one specific type of community interact with. Take the second bar (i.e., Male) as an example, which shows that the users in male-dominant communities receive and send most tags to users in the same community. Generally, the results demonstrate that more than 98% of users tend to interact with users in the same community regardless of the type of communities.

We then analyze whether the gender distribution of top-ranked users (i.e., those who interact with intra-community users the most) in a community complies with the gender that dominates the community. We examine the top 5% and top 10% users as the top-ranked users in Figure 1(b). The results show that the gender distribution of the top-ranked users generally follows the dominant gender of the community. For instance, there are on average 84.2% female users in the top 10% users of a female-dominant community. The observations suggest that with respect to influence in a gender-dominant community, users of the dominant gender are more likely to influence more members of the community.

2.3 Inter-community interaction
Next, we focus on inter-community interactions among different types of communities. Specifically, we first transform the original user-level social network into a community-level network, where nodes are communities and weighted-edges represent the numbers of interactions between members of different communities. Figure 2(a) shows the distribution of interactions among communities, where the number of interactions (i.e., weights) on each edge is considered. We find that for all types of communities, users have
3 THE DIM PROBLEM AND ALGORITHM

3.1 Problem formulation

In this paper, we aim to solve the Disparity Influence Maximization (DIM) problem, which is formally defined as follows.

**Definition 3.1 (DIM [22]).** Given a social network \( G = (V, E) \), a diffusion model, a parameter \( k \), a target gender ratio \( \zeta \), and an error margin \( e \), DIM finds a seed group \( S \subseteq V \) with \( |S| = k \) to maximize the influence spread with the constraint that the ratio of the target gender in the influenced users is \( \zeta \) within an error margin \( e \).

3.2 Algorithm

Leveraging the observations from Section 2, we propose Community and Gender-Aware Seeding (CGAS) to solve DIM. As seeding algorithms that are unaware of genders fail to achieve the specified influenced ratio of the target gender \( \zeta \), CGAS proposes a swapping mechanism to refine the seed group by evaluating users’ influence on different genders. To exploit homophily, CGAS introduces the Gender-aware Potential Influence (GPI) by summing up the intra- and inter-community influence on some gender that the neighbors of this gender can make. CGAS exchanges seeds and non-seeds according to their GPI in iterations aiming get closer to \( \zeta \) while ensuring a large influence spread. In the following, we first formally define GPI and then explain the swapping mechanism in detail.

To evaluate one’s influence on different genders, CGAS defines the Gender-aware Potential Influence (GPI) measure. A user \( v \)’s GPI on a gender \( g \) \( \in \{M, F\} \) is the sum of the influence on \( g \) that \( v \)’s neighbors of \( g \) have. Inspired by the success of community-based algorithms [4, 7, 10, 16, 18], GPI considers the Gender-aware Community Influence (GCI) to evaluate neighbors’ influence on different genders from the intra- and inter-community aspects.

Formally, we define the GPI of a user \( v \) on a gender \( g \) as follows.

\[
GPI_g(v) = \sum_{w \in N(v) \setminus A, w \text{’s gender is } g} b_{vw} \times GCI_g(w),
\]

where \( GCI_g(w) \) is \( w \)’s GCI on \( g \) defined later, \( N(v) \) is the set of \( v \)’s neighbors, \( A \) is the set of influenced users, and \( b_{vw} \) is the weight on the edge between \( v \) and \( w \) (given by the social network).

Analogously to [16], we evaluate GCI by considering two types of users in communities. One type represents core users who only have intra-community interactions, and the other type comprises boundary users who interact with users inside and outside the community. For a core user, the GCI on a gender \( g \) is based on i) the number of users of \( g \) in their community. Moreover, we also add ii) the number of their neighbors of \( g \) to account for homophily. For a boundary user, GCI on \( g \) is determined by the influence on each community he/she interacts with. Similar to core users, GCI also considers i) the average number of users of \( g \) in the communities that a boundary user interacts with and ii) the number of his/her neighbors of \( g \). As observed in Section 2.3, users in different types of communities have diverse patterns in the type of communities they interact with, GCI further takes iii) the number of \( g \)-dominant communities he/she interacts with into account. Therefore, the GCI of a user \( v \) on a gender \( g \) is defined as follows.

\[
GCI_g(v) = \begin{cases} 
U_g(v) + D_g(v) & \text{if } v \text{ is a core user} \\
\alpha \cdot AU_g(v) + D_g(v) + C_g(v) & \text{otherwise}
\end{cases}
\]

where \( U_g(v) \) is the number of users of \( g \) in \( v \)’s community, \( D_g(v) \) is the number of \( v \)’s neighbors of \( g \), \( AU_g(v) \) is the average number of users of \( g \) in the communities \( v \) interacts with, and \( C_g(v) \) is the weighted number of communities \( v \) interacts with and the weight of each community is the fraction of users of \( g \). Besides, as users tend to interact more with intra-community users (observed in Section 2.2), \( AU_g(v) \) may overestimate \( v \)’s influence and is adjusted by a parameter \( 0 < \alpha \leq 1 \) reflecting the ratio of inter-community interactions to all interactions.

Equipped with GPI, CGAS applies the swapping mechanism to refine the seed group by iteratively exchanging seeds and non-seeds. Let \( S_0 \) denote the initial seed group generated by an arbitrary, possibly non-gender-aware, seeding algorithm. For each iteration \( i \geq 1 \), CGAS estimates the influence spread of \( S_{i-1} \) on each gender to derive the influenced ratio of the target gender \( r_{i-1} \). Based on the comparison between \( r_{i-1} \) and \( \zeta \) (defined in Definition 3.1), CGAS determines the gender that should be mainly influenced in this iteration \( i \), denoted as \( g_i \). Then, CGAS chooses \( n \) seeds from \( S_{i-1} \) with the lowest \( GPI_{g_i} \) as out-candidates and \( n \) nodes from \( V \setminus S_{i-1} \) with the highest \( GPI_{g_i} \) as in-candidates to form \( n^2 \) exchange pairs, where \( n \) is a parameter to control the number of exchange pairs. Specifically, CGAS forms an exchange pair by one in-candidate and one out-candidate and estimates the influence spread on each gender considering \( S_{i-1} \) is updated by this exchange pair, i.e., removing the out-candidate from the seed group and adding the in-candidate into the seed group. Consequently, CGAS selects the exchange pair with the largest influence spread on \( g_i \) to update \( S_{i-1} \) as \( S_i \). The
swapping mechanism continues until $r_i$ reaches $\zeta$ within the error margin $\epsilon$ or the maximum iteration $i_{\text{max}}$ is reached, i.e., $i = i_{\text{max}}$.

4 EXPERIMENTS

4.1 Setup

Datasets. We first use the tag interactions on the Facebook dataset (Section 2.1) to evaluate the performance of CGaS. Furthermore, we construct the following synthetic dataset to illustrate our approach on a smaller network. As there are more females than males in the Facebook dataset (i.e., the female ratio is 60%), we apply a modified stochastic block model [6] to generate a synthetic dataset with a community structure that contains more males than females. This dataset consists of four communities with 28, 20, 22, and 30 users, and the corresponding female ratios are 0.8, 0.5, 0.25, and 0.75, respectively. In other words, the synthetic dataset has 60 males and 40 females as seeds according to the Target HI-Index scores, where the probabilities of having intra- and inter-community interactions are chosen in ranges $[0.7, 0.8]$ and $[0.01, 0.03]$, respectively.

Baselines. We use two non-gender-aware seeding algorithms and two gender-aware seeding algorithms for comparison. i) Agnostic seeding (AN) [20] selects the top-ranked users as seeds according to the number of users’ interactions. ii) CELF [11] greedily selects the users with the maximum marginal gain on the influence spread as seeds. iii) Diversity seeding (DV) [20] selects the top-ranked males and females as seeds according to the number of users’ interactions, where the female ratio of the seed group is learned from a scaling function $\zeta$ and the female ratio of AN’s seed group. iv) Disparity seeding (DP) [22] selects the top-ranked males and females as seeds according to the Target HI-Index scores, where the female ratio of the seed group is searched between the specified female ratio $\zeta$ and the female ratio of AN’s seed group.

4.2 Results

Table 1 lists the female ratio of the influenced users and the influence spread achieved by different algorithms on the Facebook and synthetic datasets. The female ratios with underlines represent the success of achieving $\zeta$ within the error margin $\epsilon$. While the spreads with bold are the maximum spread among the algorithms having female ratios with underlines. Note that we vary $\zeta$ between $[0.4, 0.7]$ and $[0.3, 0.6]$ for the Facebook and synthetic datasets, respectively, since their dominant genders are different. From the results, we have three observations. (1) CGaS can approximate $\zeta$ based on the seed groups obtained by AN and CELF, showing the applicability of CGaS to various seeding algorithms. (2) DV fails to achieve $\zeta$ within $\epsilon$ and has moderate errors only when $\zeta$ is close to the female ratio in the population (i.e., 0.6 and 0.4 in the Facebook and synthetic datasets, respectively). By contrast, AN+CGAS, CELF+CGAS, and DP deviate least from $\zeta$. (3) Although DP has small errors, AN+CGAS and CELF+CGAS always exhibit a much larger influence spread than DP while ensuring $\zeta$ is reached, since CGaS exploits the intra- and inter-community influence to evaluate the users’ influence. Specifically, CELF+CGAS achieves more than two times the influence spread of DP on the Facebook dataset.

Table 1 further presents the number of iterations required by CGaS to approach $\zeta$. As $\zeta$ deviates more from the gender distribution of the population, more iterations are required. Since non-gender-aware seeding algorithms usually yield the gender distribution in the influenced users following that in the population, a larger difference between $\zeta$ and the gender distribution of the population results in more efforts to adjust the seed group. For example, CELF+CGAS is unable to reach $0.4 \pm 0.01$ within $i_{\text{max}} = 20$.

5 CONCLUSION

Motivated by the prevalent community structure and the asymmetric influence of different genders in social networks, we conducted a first-of-its-kind gender-aware community analysis and presented a novel seeding algorithm to promote the information spread on the target group. We studied how the community structure is affected by the gender distribution and showed that many communities have a strong affinity to a single gender. Secondly, we designed a community-gender-aware algorithm that achieves a target ratio of information spread by iteratively adjusting the seeding selection based on the community-gender structure. We evaluated the proposed seeding algorithm against the state-of-the-art gender-aware seeding algorithms on both synthetic graphs and a Facebook trace. The results demonstrate that the proposed community-gender aware seeding algorithm achieves the target influence ratio while maximizing the information spread.

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