Fair2Vec: Learning Fair and Topic-Aware Representations for Influencer Recommendation

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Abstract

Balancing influence maximization with demographic fairness remains a critical challenge in recommendation systems. Existing methods either ignore topic-sensitive fairness or rely on heuristic approximations that lack scalability. We propose *Fair2Vec*, a novel framework to jointly recommend (1) top-$\boldsymbol{k}$ influencers, (2) top-$\boldsymbol{r}$ topics, and (3) ensure the influenced population's demographic distribution aligns with the broader topic-specific community. *Fair2Vec* leverages topic-aware embeddings to model influence dynamics and fairness constraints, eliminating error-prone multi-hop computations. By restructuring networks as bipartite graphs, it reduces time complexity compared to state-of-the-art heuristics. Experiments on *Meetup*, *Yelp*, and *DBLP* datasets demonstrate *Fair2Vec's* superiority: it achieves higher fairness and greater influenced populations than baselines. Our work bridges the gap between scalable influence maximization and topic-aware fairness in recommendations, offering actionable insights for platforms aiming to foster inclusive engagement while preserving relevance to user interests.

Keywords: Influence, Fairness, Embedding, Topic, Social networks

1 Introduction

Influence Maximization (IM) [1] aims to identify a small set of individuals who can maximize the spread of influence in a network. Traditional IM models assume a uniform influence across all topics, but [2] introduced topic-aware IM, showing that influence varies depending on the topic. For example, on LinkedIn, a professional known for insightful posts on data science and analytics may have a large following and spark wide discussions in tech circles, yet may not resonate as strongly with audiences interested in topics like HR practices, personal branding, or early-career guidance. This underscores the necessity of topic-aware influence maximization (*TAIM*), where both influencers and the topics they dominate must be jointly optimized.

The need for fairness in Topic-Aware Influence Maximization (*TAIM*) grows critical when addressing demographic disparities in topic engagement. Prior work [3, 4] proposes recommending influencers such that the influenced population's sensitive attribute distribution (e.g., gender ratio) matches the entire population's distribution. However, in *TAIM*, topics often exhibit distinct demographic skews. On platforms like LinkedIn, interest in topics such as leadership, entrepreneurship often sees greater participation from male professionals, while discussions around work-life balance, wellness, or diversity in the workplace tend to engage more female users. For instance, if posts on diversity and inclusion naturally attract 80% female engagement, then strictly enforcing a balanced gender ratio (say, equal fraction of male & female) while recommending such content could result in targeting disinterested male audiences, thereby reducing interaction quality and content relevance. In contrast, aligning recommendations with topic-specific audience distributions (e.g., $80 : 20$) ensures authenticity, relevance, and a more inclusive approach that honors genuine interests. Failing to proportionately represent female audiences in topics where they are naturally more engaged (e.g, work-life balance) leads to knowledge access inequality, where underrepresented groups receive less exposure to meaningful, career-enhancing content. This can limit professional growth, reduce visibility in key domains, and reinforce existing inequities within the platform's ecosystem. Promoting fairness in *TAIM* through topic-aware strategies helps bridge such divides and fosters a more equitable professional community.

Prior *TAIM* methods [2, 5] assume fixed topics and ignore demographic fairness within influenced populations, whereas fairness-aware IM frameworks [3, 4, 6] neglect topic-specific fairness. Two additional limitations hinder current approaches: *Heuristic Inefficiency:* Several methods [2] estimate influence probabilities using arbitrary heuristics or noisy historical interaction logs, leading to unreliable outcomes. Furthermore, as network depth increases, computing influence spread across multiple hops becomes computationally intractable [5], severely limiting scalability. To address these issues, recent works [7, 8] have represented influence relationships using embeddings. Embedding-based methods offer key advantages: for instance, if an influencer u impacts v indirectly through multiple hops, their embeddings can estimate the probability of influence with higher accuracy and lower computational costs. Moreover, embeddings can effectively quantify the influence of individuals who exert similar levels of influence among their respective followers. However, existing embedding-based methods do not incorporate fairness considerations. Though adversarial methods [9,10] merge fairness with embeddings, they assume topic-invariant influence, ignoring how an influencer's efficacy varies across topics like *Sports* versus *Art*. This gap underscores the need for a novel approach that simultaneously optimizes influence spread and ensures fairness across recommended topics.

In this paper, we propose *Fair2Vec*, a method that computes topic-wise embeddings for influencers and followers to recommend: (i) the top-k influential members

I_k, and (ii) the top-r influence topics T_r, ensuring that I_k is both highly effective for T_r and fair with respect to sensitive attributes (e.g., gender) across the influenced population for each $t \in T_r$. *Fair2Vec* comprises three main components. First, we identify potential influencers and compute a *topic-wise fairness score*, measuring how closely the sensitive attribute distribution in their influenced population matches that of the broader topic-specific audience. Second, we introduce a *multi-task embedding model* to learn topic-wise embeddings, where the fairness score acts as a penalty that limits each influencer's impact, thereby guiding influence allocation. These embeddings are used to estimate influence probabilities, eliminating reliance on heuristic assumptions. Finally, we construct a *bipartite graph* where edge weights capture both influence probability and fairness. We then solve an optimization problem to recommend I_k and T_r that maximize influence while enforcing fairness constraints per topic. By embedding fairness directly into the learning process and avoiding multi-hop computations, *Fair2Vec* offers both scalability and stronger fairness guarantees than prior methods. We evaluate *Fair2Vec* on three real-world datasets—*Meetup* (event-based), *Yelp* (location-based), and *DBLP* (citation network)—demonstrating superior influence spread and fairness over baselines.

2 Related work

Influence maximization: [1] introduced the problem of influence maximization where the author proposed 2 greedy algorithm (i) Independent cascade and (ii) Linear threshold to find the influence spread. After this, many algorithms like [11] are developed to reduce the time complexity. But all this algorithm depends on a diffusion graph with edges weighted on a power of influence; this influence power is found by either using historical logs or by making simple assumptions. These algorithms do not consider the impact of unfairness on the influenced population and also did not capture the effect of topics on influence maximization.

Topical influence in social networks: This section discusses work on identifying topical influencers in social networks. Studies such as [2], and [12] address influence propagation given input topics (queries), aiming to find topic-specific influencers. [5] and [13] focus on finding the top-k influencers and the best r influence tags for platforms like *Meetup* and *Yelp*. Notably, these studies do not consider fairness and treat all influencers equally.

Fair influence maximization: Several works have integrated fairness into influence maximization. Tsang et al. [3] introduced fairness in resource allocation, inspiring fairness-aware models. Techniques include integer programming [4], welfare optimization [6], and reinforcement learning [14]. Adversarial [9] and clustering-based methods face challenges with multi-attribute fairness. Lin et al. [15] adapted the RRS algorithm for fair seed selection. Deep learning with historical cascades [16] and concave fairness frameworks [17] struggle with dynamic environments. Community-based strategies [18] enhance fairness but rely on rigid structures. Optimization approaches like multi-objective models [19] improve fairness but increase computational cost. Hypergraph [20] and counterfactual graph-based methods [21] offer alternatives, though they require careful tuning. These approaches underscore the trade-off between fairness, scalability, and adaptability.

3 Motivation study and problem statement

First, we introduce all the datasets, then we conduct some pilot studies to highlight the limitations of potential influencers identified using the standard algorithm [22], and finally, we describe the problem statement.

3.1 Dataset

In this paper, we introduce three different social network dataset namely *Meetup* (EBSN), *Yelp* (LBSN), and *DBLP* (citation network). *Meetup* is a popular event based social networking (EBSN) portal that facilitates hosting events in various localities around the world [22]. *Meetup* groups are organized into 33 official categories e.g., *Career and Business*, *Technology* that define their general focus. Each group hosts events on specific topics, such as *Accounting* or *Drawing*, which reflect the interests of both the group and its members. Upon joining, members select tags or topics that reflect their personal interests. These topics help personalize recommendations and connect members with relevant communities and events. Meetup event attendees are users who responded "Yes" to the event RSVP, as indicated by their RSVP status ("Yes", "No", or "Maybe"). In this paper, we focus on groups in Chicago under the 'Career and Business' category (767 groups, avg. 83 events). *Yelp* is a location-based social network where users post reviews about restaurants. Each review is associated with specific cuisines (e.g., 'Chinese', 'Pizza'), which we treat as topics. Our analysis focuses on 267 restaurants in San Francisco, comprising approximately 1.9 million reviews. The network includes around 13,000 users and 53 distinct cuisine-based topics. *DBLP* is an academic citation network where topics correspond to research keywords (e.g., 'Information Flow', 'Security'), extracted from paper metadata. To infer the gender of citing authors, we use the first author's name from each citing paper, applying probabilistic methods based on the SSA baby name dataset and the Gender API. The dataset consists of approximately 95 topics and 900 authors.

3.2 Motivation and pilot study

This section presents the datasets and a pilot study motivating our fairness-aware approach.A member u_i is labeled a potential influencer if another member u_j RSVPs to the same event within five hours of u_i's RSVP.[1] If this pattern occurs for at least four events, u_i is said to influence u_j on the associated event topics t_e. In this case, we assign u_i the *influence topic* t_e and denote the influence relationship as $u_i \xrightarrow{t_e} u_j$. The set of all such potential influencers is denoted by U_N. For each $u_i \in U_N$, we define their *direct followers* as $F_i = \bigcup_j u_j$, where $u_i \Rightarrow F_i$ implies that u_i has influenced all users in F_i. The size of this set, $|F_i|$, quantifies the *influence capacity* of u_i. Here in the pilot study, we consider the number of direct followers as influence capacity, however, in the developed methodology, we implement a standard procedure to compute the influenced population (direct and indirect).

First, we handpick top-20 potential influential members $U_N(N = 20)$ of *Meetup* for the category *Career and Business* in *Chicago* city based on their influence capacity and highlight their limitations as influential members.

(a) Capacity of the influential member varies across event topics: We analyze a potential influencer $u_i \in U_N$ attending events of a *Meetup* group G_i, which hosts topics like {'Women Profession', 'IT', 'Fundraising', 'Investing'}. Fig. 1a shows

[1] We follow the empirically validated threshold used in [22].

the event topics t_e (x-axis) attended by u_i. The blue bar represents the fraction of u_i's followers $f_i \in F_i$ attending each event ($u_i \xrightarrow{t_e} f_i$), while the green bar shows the fraction of event attendees who are u_i's followers. This can be observed that event topics like 'IT' and 'Fundraising' attract significantly more followers than 'Women Profession' and 'Investing' (p-value < 0.05, two-sided t-test). This suggests that the effectiveness of an influencer can vary across topics, emphasizing the need to identify the most suitable event topics while detecting influential members in *Meetup*.

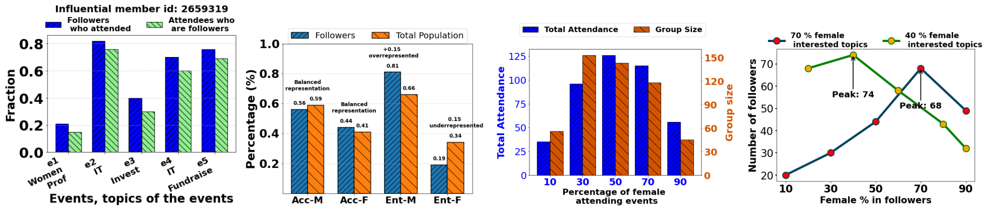
(b) Fairness of the influential member varies across event topics: We analyzed a potential influential member u with two influence topics: *Accounting* and *Entrepreneurship*. To assess gender fairness, we compared the gender distribution of u's followers for each topic with that of the broader *Meetup* population in Chicago, based on event attendance. As shown in Fig. 1b, the distribution for *Accounting* aligns closely with the population, indicating fairness. However, for *Entrepreneurship*, only 0.19% of u's followers were female, compared to 0.34% in the general population—revealing gender bias. This underscores the importance of evaluating fairness on a topic-by-topic basis to understand an influential user's reach.

(c) Bias in event attendance are detrimental for groups: Our pilot study reveals that the underrepresentation or overrepresentation of any gender becomes detrimental for the *Meetup* groups. In Figure 1c, we plot the performance of the *Meetup* group (as event attendance and group size) with respect to fraction of female attendees across events hosted by those respective *Meetup* groups. We observe that the event attendance and group size drop as female (or male) presence is marginalized (around 10%) in those respective *Meetup* events. This clearly indicates that if event attendance is dominated by one gender, it can make other gender feel unwelcome, reduce interest in the event, and eventually lead to a decline in group performance.

(d) Strict enforcement of fairness is detrimental for influence capacity: We conduct a study to determine the optimal proportion of females (or males) in an influencer's follower population to maximize influence capacity. We select six female-biased topics (e.g., *Beauty Products*, *Fashion*) where roughly 70% of interested users are female and cluster influencers by their female follower fractions (10%–90%). Figure 1d plots the average influence capacity (y-axis) against the fraction of females present as their followers (x-axis). We repeat this for several male-biased topics (female interest $\approx 40\%$). In both cases, influence capacity peaks when the follower gender ratio is close to the fraction of females interested in those topics (say, 70% or 40%). Notably, enforcing equal gender balance can reduce influence, as it introduces disengaged participants. This may stem from the fact that bringing more men into female-oriented topics can result in disengaged participants, reducing overall influence.

3.3 Problem statement

Consider a *Meetup* group G located in city $\mathcal{C} \in C$. Objective of this paper is to develop $Fair2Vec$, which recommends top-k of influential members I_k, who may influence the *Meetup* members, in city $\mathcal{C}$ to attend the events hosted by the group G to make them popular. For each recommended influencer member $I_i \in I_k$, we also recommend top-r topics T_r which are most effective for I_i to influence her followers to attend the *Meetup* events. Importantly, $Fair2Vec$ ensures gender fairness among the influenced population. Precisely, for each recommended topic $T_i \in T_r$, the gender distribution of the influenced population must closely match the corresponding distribution in the *Meetup* population interested in topic T_i.



(a) (b) (c) (d)

Fig. 1: **(a) Capacity of influential member varies across various topics (b) Gender representation in topic *Entrepreneurship* and *Accounting.* Males are overrepresented in *Entrepreneurship* (Ent), while *Accounting* (Acc) shows balanced representation. (c) Impact of Declining Female Participation on Group Dynamics. (d) Influence peaks when the gender ratio in the followers aligns with the topic's natural audience (e.g., 70% female).**

This framework extends naturally to other platforms. For example, in *Yelp*, Fair2Vec recommends top reviewers (influencers) and top cuisines (topics) to attract customers to restaurants, while ensuring the gender distribution of influenced customers aligns with the demographic composition of users interested in each cuisine. Similarly, in *DBLP*, it recommends top authors (influencers) and research areas (topics) to promote citation influence, ensuring that the gender ratio of authors citing the recommended researchers matches the inherent demographic distribution of each research topic (e.g., male/female ratios in research topic 'Security').

The crux of $Fair2Vec$ relies on the correct learning of the influence intensity that one influential member exerts on her direct and indirect followers. We aim to first represent the influence capacity of an influencer with the help of an embedding, which keeps both her topic awareness and gender fairness in consideration. Similarly, we model the susceptibility of a member to influence through an embedding that reflects their likelihood of being influenced by others. This formulation is applied across multiple real-world datasets, including *Meetup*, *Yelp*, and *DBLP*, each representing distinct types of networks. Finally, these two embeddings—one for the influencer and one for the follower—are used together to compute the overall influence intensity that an influencer exerts on both her direct and indirect followers.

4 Development of *Fair2Vec*

In this section, we describe the development of *Fair2Vec*[2]. While the framework generalizes across platforms, we detail its implementation for *Meetup* below, with analogous steps applicable to other datasets like *Yelp* or *DBLP*.

4.1 Identifying group aligned potential influencers

First, we identify all the event topics T_G that are aligned with *Meetup* group G. For that, we extract all the past hosted events E_G of G, and from each event's textual description, we extract the most relevant keywords using *YAKE* [23]. We populate T_G with the top 20 most frequently occurring keywords of events E_G[3].

[2] Our code is publicly available at https://github.com/ArpanDam/fair-influence-embedding
[3] We also include few additional topics from other events, which are semantically close to T_G.

Next, we identify all the group aligned potential influencers U_C, who influences other *Meetup* members via group aligned topics T_G. For that, first we identify all the potential influencers U_N following the procedure explained in Sec 3.2, and then find the subset of potential influencers ($U_C \subseteq U_N$), who influence other *Meetup* members exclusively on topics $t_j \in T_G$ that align with the group G's interest. For each potential influencer $u_i \in U_C$, the influence context A_{u_i} includes all members influenced by u_i on a specific topic t_j, encompassing both direct followers F_{u_i} and indirect (multi-hop) followers. For example, if u_1 influences u_2 on the topic *IOT*, and u_2 subsequently influences u_3 on the same topic, then influence context of u_1 becomes $A_{u_1} = \{u_2, u_3\}$. The size of A_{u_i} quantifies u_i's influence capacity on topic t_j.

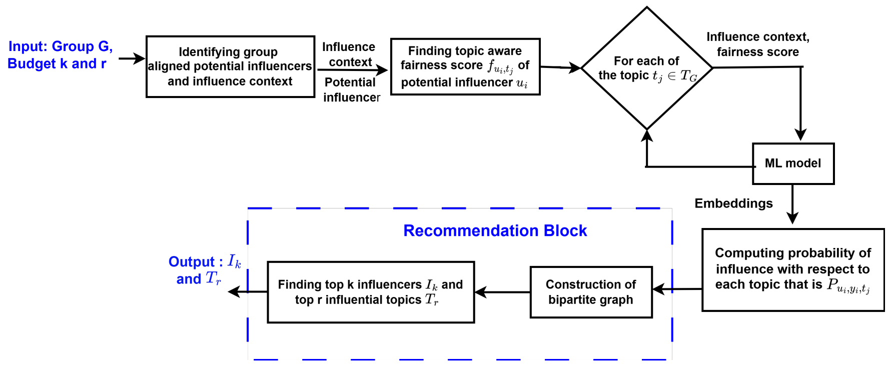


Fig. 2: **Flowchart of *Fair2Vec*.**

4.2 Estimating fairness of a potential influencer

As discussed in Section 3.2, fairness of a influencer with respect to a sensitive attribute (say, gender) may vary significantly across different topics. Fairness of an influencer u_i is measured observing the fairness ratio $\mathcal{F}_j$ across various sensitive attributes j. We define fairness ratio $\mathcal{F}_j$ as the ratio between the fraction of a sensitive attribute j (say female) present in the influence context of u_i for topic t_j (say, V_j), and the fraction of the same sensitive attribute j (say female) present in overall Meetup population interested in topic t_j (say, E_j). For a perfectly fair influencer u_i, one should observe $\mathcal{F}_i = \frac{V_j}{E_j} = \mathcal{F}_j = \frac{V_i}{E_i}$ for various sensitive attributes i (say male), j (say female) etc [3]. Higher diversity in the fairness ratio $\mathcal{F}_j$ $\forall j$ points to an unfair influencer u_i. Hence to quantify fairness of a influencer u_i, we compute the standard deviation σ and the mean μ of the fairness ratios $\mathcal{F}_j$ across various sensitive attributes j and then derive the coefficient of variation $D_{u_i} = \frac{\sigma}{\mu}$, which measures the degree of unfairness of u_i. Subsequently, we define the normalized fairness score $f_{u_i} = \frac{2}{1+\exp(D_{u_i})}$ of u_i, where fairness score closer to 1 indicates a fair influencer, while a lower score suggests greater unfairness. For each group-aligned influencer u_i, we obtain a fairness score vector f_{u_i,t_j}, where each element represents the fairness score of u_i for a specific influence topic $t_j \in T_G$.

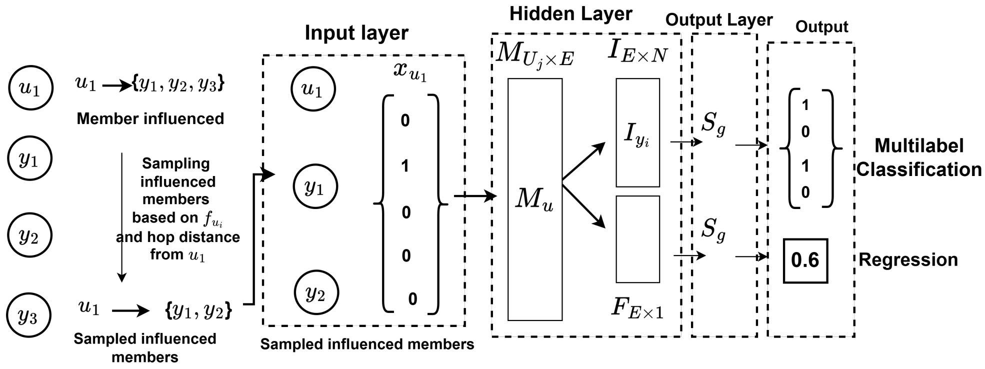


Fig. 3: **Multitask neural network to find embedding where u_1 is a potential influencer. u_1 is influencing $\{y_1, y_2, y_3\}$, f_{u_1} is 0.6 which is the fairness score of u_1. Influenced members are sampled based on f_{u_1} and the model has to predict the sampled influenced users and f_{u_1}.**

4.3 Learning fairness aware influencer embeddings

In this section, we implement a multi-task neural network model (see Fig. 3) to learn the capacity of an influential member $u_i \in U_C$ to fairly influence the members in her influence context A_{u_i}. We represent the influence capacity of u_i with the help of embedding M_{u_i}. The key idea of this MTL model is to penalize an unfair influencer u_i by downsampling her influence context based on its topic aware fairness score f_{u_i,t_j}. Precisely, given an influencer u_i with *influence topic* t_j, her influence context is downsampled to $A^s_{u_i}$ by selecting $|A_{u_i}| \times f_{u_i,t_j}$ nodes from its influence context $|A_{u_i}|$. We prioritize retaining the followers who are closer in hop distance to u_i, as they are more likely to be directly influenced. The probability of retaining a node $y \in A^s_{u_i}$ in the sampled influence context $A^s_{u_i}$ is determined by its hop distance from u_i, with farther nodes being more likely to be removed. This ensures that the fairness score acts as a penalty for an unfair influencer while preserving strong direct and near-indirect influence relationships. The proposed MTL model simultaneously conducts two separate tasks: (a) given a potential influential member u_i, the model predicts its direct and indirect influenced members (sampled influence context $A^s_{u_i}$), and (b) estimates the fairness score (f_{u_i,t_j}) of u_i. Here, estimating the fairness score is a regression task, whereas predicting the influenced members is a multi-label classification task.

4.3.1 Model construction

We train the multi-task learning (MTL) model for each group-aligned topic $t_j \in T_G$, designed to process two inputs: (1) pairs of influential nodes and their sampled influence contexts and (2) fairness scores. For a topic t_j, let $A^s_{u_i} = \{y_1, y_2, \ldots, y_m\}$ represents the (down)sampled influence context of influencer u_i. The first input is encoded as $X^i = \{(x_{u_i}, x_{A^s_{u_i}})\}$, where $x_{u_i} \in \mathbb{R}^{|U_j|}$ is a one-hot vector for u_i, $|U_j|$ denotes the number of topic-specific influencers, and $x_{A^s_{u_i}} \in \mathbb{R}^N$ encodes the downsampled influenced context $A^s_{u_i}$) of size N. The second input, $X^c = \{(x_{u_i}, f_{u_i,t_j})\}$, pairs u_i with its fairness score f_{u_i,t_j}. The MTL architecture (Fig. 3) consists of a shared embedding layer $\mathbf{M} \in \mathbb{R}^{|U_j| \times E}$ with embedding dimension[4] $E = 50$, where $M_{u_i} = x_{u_i}\mathbf{M}$ generates influencer embeddings. Task-specific layers include $\mathbf{I} \in \mathbb{R}^{E \times N}$ for influence prediction (yielding embeddings I_{y_i} for influenced members y_i) and $F \in \mathbb{R}^{E \times 1}$ for fairness score estimation, enabling joint optimization of influence spread and demographic fairness through shared representations.

Loss function: To predict the influenced members $A^s_{u_i} = \{y_1, y_2, \ldots, y_m\}$, we apply the sigmoid activation function S_g at the output layer. Since this is a multi-label classification task, we use the binary cross-entropy loss function L_e. For estimating the fairness score, we employ the Mean Squared Error (MSE) loss function L_m. The total loss L that we aim to minimize is the sum of both components $L = L_e + L_m$.

Estimating fair influence capacity: Let u_i be a potential influencer with an associated influence topic t_j. If u_i influences the member y_i to participate in events related to t_j, we apply a sigmoid transformation on the dot product of M_{u_i} and I_{y_i} to compute p_{u_i,y_i,t_j}. This value represents the capacity of u_i to influence y_i through the topic t_j.

$$p_{u_i,y_i,t_j} = S_g(M_{u_i} I_{y_i}) \tag{1}$$

For each of the topics $t_j \in T_G$ we train the MTL model and compute the capacity of influence p_{u_i,y_{u_i},t_j} for all $u_i \in U_C$, where y_{u_i} is the influence context of u_i with influence topic t_j. The training is conducted for each of the topics $t_j \in T_G$. The training time is $|T_G| \times |W| \times N$ where $|T_G|$ is the number of group-aligned topics, W is the average number of sampled members influenced per topic, and N is the total number of members in $Meetup$.

4.4 Influencer recommendation

Finally, leveraging the influence capacity of influencers, we recommend top k fair influencers and their respective top r influence topics. First, we construct a weighted bipartite graph.

(a) Construction of bipartite graph: We construct an attributed bipartite graph $G(U_C, A_{u_i}, E)$, where the first partition contains the group aligned potential influencers U_C, and the second partition contains the influence contexts A_{u_i}. E denotes the directed links from potential influencers $u_i \in U_C$ to its respective followers A_{u_i}. Each link of this graph contains two different attributes: (i) The influence topic t_j, through which influential member u_i influences y_i to attend an event on topic t_j. (ii) the probability p_{u_i,y_i,t_j}, representing the capacity of an influencer u_i to influence the member y_i on topic t_j (from Eq. (1)). A potential influencer of the first partition may appear as a follower in the second partition.

(b) Recommending top k influencers and top r influential topics: We employ the Independent Cascade (IC) [1] on each potential influencer $u_i \in U_C$ of the first partition to obtain the influenced population $\widehat{A}_i$. Our framework ensures fairness by integrating fairness scores directly into the influence capacity p_{u_i,y_i,t_j} of the bipartite graph. We greedily select the top-k influencers I_k based on the influenced population $\widehat{A}_i$, prioritizing those with both high influence potential and fair audience alignment. Unfair influencers receive lower capacity due to their topic-specific fairness penalties f_{u_i,t_j}, reducing their likelihood of being selected. Once I_k is selected, we find the influenced population using IC, then we analyse the edges from I_k to the influenced

[4]Embedding size empirically set to 50.

population and greedily select the top-r influence topics T_r that maximise the influenced population. The final output consists of the top-k fair influencers I_k, their top-r influence topics T_r, and the total influenced population $\widehat{A}_{k,r}$.

Time complexity: Selecting the top-k influencers using the greedy Independent Cascade (IC) model takes $\mathcal{O}(k \cdot |U_C| \cdot m)$ time, where $|U_C|$ is the number of group-aligned influencers and m is the number of edges. Identifying the top-r topics adds $\mathcal{O}(k \cdot m)$, but as $|U_C| \gg 1$, the total simplifies to $\mathcal{O}(k \cdot |U_C| \cdot m)$. This offers notable efficiency over traditional multi-hop methods by focusing only on direct, fairness-adjusted influence pathways, ensuring scalability.

5 Experimental setup

5.1 Performance metrics

Here, we find out the top k fair influencer I_k and top r influence topics T_r and then evaluate the performance of the influencer and topics based on two criteria: (1) Fraction of influenced population and (2) Fair presence of the influenced population across various topics.

Fraction of influenced population: For a *Meetup* group or *Yelp* restaurant, we compute the fraction of users influenced by I_k using the Independent Cascade (IC) model [1]. For *Meetup*, this reflects event attendance; for *Yelp*, restaurant visits. Results are averaged across all groups/restaurants in the same category to ensure robustness.

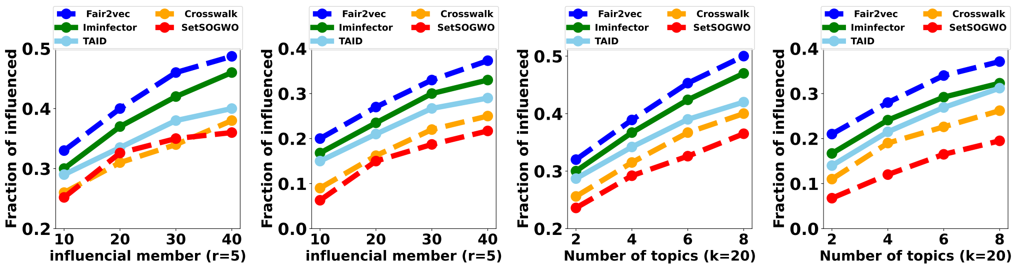
Measuring fairness: To quantify fairness across recommended topics, we use two metrics: **(a) L1 Norm**: L1 norm [4] measures the absolute disparity in influence distribution across sensitive attributes. It is computed as: $\sum_s |p_s - \bar{p}|$ where p_s is the fraction of influenced members from a particular sensitive attribute (e.g., gender), and $\bar{p}$ is the overall influenced fraction. **(b) Utility Gap**: Utility gap [6] measures the highest difference of expected influenced population between a pair of sensitive attributes. To compute the utility gap across recommended topics (e.g., t_1 and t_2), we calculate the utility gap within each topic separately and average the utility gap across all recommended topics. The final utility gap is averaged over all $t \in T_r$. Lower values of *L1 norm* and *utility gap* ensure better fairness.

5.2 Evaluation methodology

We divide the dataset into training and testing data based on their time of occurrence. For example, in *Meetup*, the groups existed from the time period 2015 to 2022. We split the lifetime of *Meetup* into two halves, considering [2015 to 2021] as training and [2021 to 2022] as testing periods. We apply MTL on the training data to learn topic-wise influence capacities between influencers and followers. Using this, we construct a bipartite graph on the test data and identify the top-k influencers. For *Yelp*, we similarly divide the dataset based on the timing of reviews. We consider the period from 2017 to 2020 as the training set and 2020 to 2022 as the testing set. For the *DBLP* dataset, we utilized citation information, specifically the year in which author A cited a paper authored by B. The training data spans the period from 2000 to 2010, while the testing data covers the years 2010 to 2013.

5.3 Baseline algorithm

We implement the following baselines to compare the performance of our proposed algorithm. **(a)** *TAID* [5] Here, the authors have proposed a heuristics approach to find



(a) *Meetup* (b) *Yelp* (c) *Meetup* (d) *DBLP*

Fig. 4: (a) - (d) shows the effectiveness of I_k in terms of fraction of influenced.

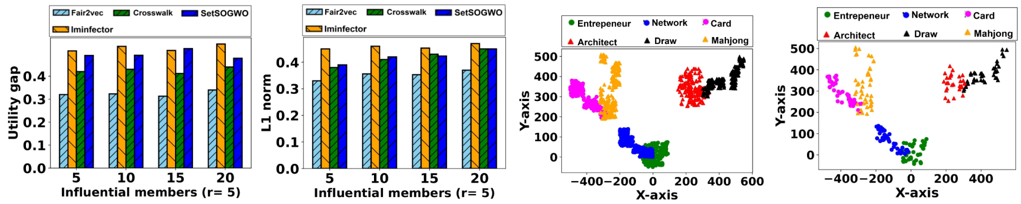
top k influencers and top r topics. **(b)** *Iminfector* [7] Here, the author has proposed a Multi-task learning model to find embeddings of influencers and subsequently find top k, influential members. *TAID* and *Iminfector* process doesn't consider fairness while recommending influential users.**(c)** *SetSOGWO*: It is a single-objective version of SetMOGWO [24], which is developed based on gray wolf optimization [25]. Here the objective is to find fair influencers while maximizing the fairness [3]. Here, we assign the probability of influence based on historical logs. **(d)** *Crosswalk* [10]: It is a random walk-based graph representation method, which enhances fairness by re-weighting the edges between nodes from different groups. We initialize the edge weights based on the in-out degree. Since these baselines mentioned above do not recommend topics, we adopt these models by finding top k influencers and then greedily selecting the r topics that give the highest influence spread from the k influencers.

6 Performance evaluation

In this section, we evaluate the performance of *Fair2Vec* from various perspectives.

6.1 Overall evaluation of $\boldsymbol{Fair2Vec}$

(a) Fair2Vec optimizes the influenced population: In Fig 4, we plot the fraction of influenced population $\widehat{A}_{k,r}$ of the recommended top-k influencers I_k. For the sake of brevity and to avoid repetition, we present results for only a subset of the datasets. Fig. 4a and 4b shows that for *Meetup* and *Yelp*, $Fair2Vec$ outperforms the baselines in terms of the fraction of influenced population. The limitation of *SetSOGWO* and *TAID* stems from their inability to properly capture the influence capacity of the influencers, which are computed from the historical logs only, thus producing poor-quality influencers. On the other hand, Fair IM algorithm like *Crosswalk* does not explicitly capture topic-specific efficiency of the influencers, leading to suboptimal performance. Fig 4c and 4d show that $Fair2Vec$ is effective for recommending the top r topics that maximize the influence spread in *Meetup* and *DBLP* datasets.
(b) Fair2Vec maintains fairness: In Fig 5a, we show the extent of fair gender distribution of influenced population $\widehat{A}_{k,r}$ for the proposed $Fair2Vec$ against the various baseline algorithms. We demonstrate fairness with the help of (i) utility gap and (ii) L1 norm. Fig. 5a and 5b show that $Fair2Vec$ exhibits a better fairness score compared to all the baseline algorithms. The low performance of *SetSOGWO* is because



(a) *Meetup* (b) *Yelp* (c) *Meetup* (d) *Meetup*

Fig. 5: (a) (b) Figure showing *Fair2Vec* has lower utility gap and L1 norm for *Meetup* and *Yelp*, hence better fairness. (c) Different embeddings for influencers (*Meetup*) for different topics. Similar topics have embeddings close to one another and dissimilar topics have embeddings far apart. (d) Different embeddings of the same influencers for different topics.

SetSOGWO assigns influence probabilities using historical logs and overlooks topic-specific fairness, resulting in poor demographic balance in topic-wise influence. As to the embedding-based method, *Crosswalk*, the algorithm for selecting the influencers is clustering based, and it fails to properly capture the fairness aspect of the influencers.

6.2 Embedding quality of *Fair2Vec*

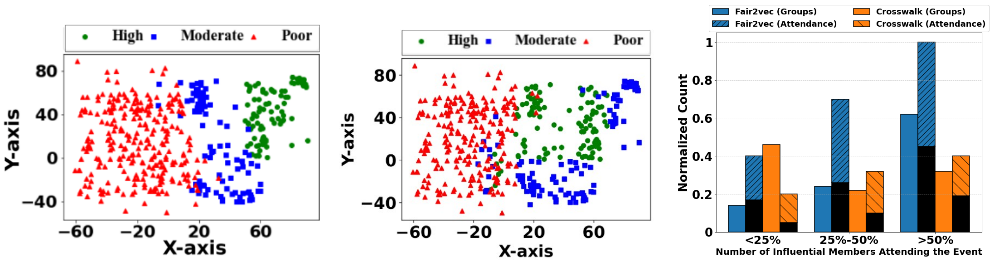
(a) Capturing topic: *Fair2Vec* learns embeddings for influencers exclusively for different topics, hence for each topic, an influencer gets an unique embedding. Fig. 5c shows the embeddings of influencers (*Meetup*) for six different topics. It is evident from Fig. 5c that for similar topics (e.g., 'Drawing' and 'Architecture'), influencer embeddings become close to each other, while for dissimilar topics (e.g., 'Drawing' and 'Networking'), influencers remain farther apart in the embedding space. This is important to note that a single influencer may have different embeddings for different topics. To illustrate this, we have taken 47 influencers common to all six topics and plotted their embeddings. Fig. 5d shows that the same influencers have different embeddings for different topics.

(b) Capturing fairness: Next, we evaluate the embedding quality in the context of fairness. We classify 624 *Meetup* influencers on the same recommended topic 'Advertising' into highly fair ($f_{u_i} > 0.8$), moderate ($0.2 < f_{u_i} < 0.8$), and poorly fair ($f_{u_i} < 0.2$) categories based on their fairness score. Fig. 6a plots the embeddings of these 624 influencers. We observe that *Fair2Vec* successfully discriminates these 624 influencers based on their individual fairness in the embedding space.

(c) Capturing influence capacity: Finally, we evaluate the embeddings in the context of influence capacity. We classify 624 *Meetup* influencers into highly, moderately, and poorly influential categories, and plot the embeddings of all these influencers in Fig. 6b. We observe that *Fair2Vec* effectively discriminates these three class of influencers in the embedding space, though some overlap occurs due to the fairness-influence trade-off.

6.3 Justifying fairness score of *Fair2Vec*

We conduct an experiment to justify the fairness score introduced in Sec 4.2. In place of topic specific computation of fairness ratio $\mathcal{F}_i$ and fairness score (f_{u_i,t_j}) for topic t_j, we compute the fairness score (f_{u_i,t_j}) based on the overall (male & female) population present in Meetup. Hence, we (re)define fairness ratio F_j as the ratio between the fraction of a sensitive attribute j (say female) present in the influence context of u_i,



(a) *Capturing fairness* (b) *Influence capacity* (c) *Fair2Vec vs Crosswalk*

Fig. 6: **(a)(b) Embeddings of influential members of *Meetup* for the topic *Advertising*: *Fair2Vec* shows good clustering in terms of fairness and influence spread. (c) Normalized group and event attendance comparison between *Fair2Vec* and *Crosswalk*, showing stronger influencer impact and follower engagement for *Fair2Vec*.**

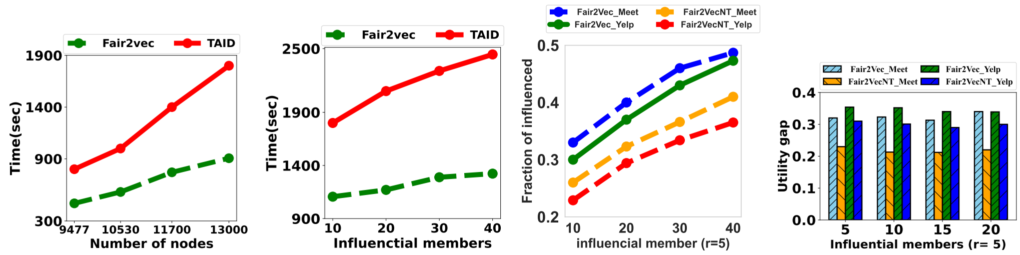
vis-e-vis the fraction of the same sensitive attribute j (say female) present in overall *Meetup* population, *irrespective of any topical interest*. Based on this fairness score, we implement a variation of *Fair2Vec* as *Fair2VecNT*. Figure 7c shows that *Fair2Vec* consistently outperforms *Fair2VecNT* in terms of influenced population on the *Meetup* and *Yelp* datasets (with the number of topics fixed at 5). This is because *Fair2VecNT* attempts to influence *Meetup* members of a specific gender (say male), who may not be interested in the given topic, leading to reduced influence coverage. Interestingly, Figure 7d reveals that *Fair2VecNT* achieves higher fairness by enforcing a uniform gender ratio across all topics. Study shows that the overall population in Meetup consists of 60% males and 40% females. *Fair2VecNT* ensures that this ratio is reflected in the influenced population, even for topics like *Beauty Product*, which may naturally skew towards females. While this promotes global gender balance, it risks misaligning with topic-specific audience dynamics.

6.4 Efficiency of *Fair2Vec* in practice

To demonstrate the practical effectiveness of *Fair2Vec*, we handpick 50 *Meetup* groups and run *Fair2Vec* and *Crosswalk* on 80% of the data (2015–2021) to recommend the top-20 influencers (I_k) with 5 topics. We then test whether these influencers attract their followers to events during 2021–2022. Fig. 6c shows that *Fair2Vec*'s influencers attended more relevant events and drove significantly higher attendance ($p < 0.05$), with shaded bars showing follower impact. Among six common influencers, topics uniquely recommended by *Fair2Vec* attracted 1.8× more users than those of *Crosswalk*. Finally, *Fair2Vec* achieves better fairness (utility gap: 0.36 vs. 0.54), confirming its ability to maximize both influence and demographic balance.

6.5 Running time of *Fair2Vec*

In Fig. 7a, we compare the training time of *Fair2Vec* and *TAID* on the *Yelp* dataset, keeping the number of influencers and topics fixed at 10 and 5, respectively. The results show that *Fair2Vec* outperforms *TAID* in terms of time efficiency. Figure 7b further demonstrates scalability by varying the number of recommended influencers k (x-axis) while fixing topics at 5. As number of influencers increase, the time required for *TAID* grows significantly faster compared to *Fair2Vec*. This is primarily because *TAID* rely on indirect link traversal whereas *Fair2Vec* reconstructs the network as a bipartite graph, which removes indirect edges and focuses solely on direct influence pathways, eliminating redundant computations.



(a) (b) (c) (d)

Fig. 7: **(a) Training time: *Fair2Vec* vs *TAID* for *Yelp*. (b) Recommendation Time: *Fair2Vec* vs *TAID* for *Yelp* (c) (d) Comparison of *Fair2Vec* with *Fair2VecNT*.**

7 Conclusion

We introduce *Fair2Vec*, a novel framework for recommending fair influencers and topics with demographic parity in influence spread. Unlike traditional influence maximization (IM) methods, *Fair2Vec* incorporates fairness directly into the influencer selection process. It computes fairness scores based on demographic influence (e.g., male and female) and uses a multi-task learning model to predict both influence reach and fairness. A fairness-aware downsampling method penalizes unfair influencers. Topic-specific embeddings for influencers and followers help estimate influence probabilities, forming a weighted bipartite graph. We then greedily select the top k influencers and r topics. Experiments on real-world datasets (*Meetup*, *Yelp*, *DBLP*) demonstrate that *Fair2Vec* outperforms baselines in both influence spread and fairness.

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