A Graph-Based Approach for Mitigating Multi-Sided Exposure Bias in Recommender Systems

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Fairness is a critical system-level objective in recommender systems that has been the subject of extensive recent research. A specific form of fairness is supplier exposure fairness, where the objective is to ensure equitable coverage of items across all suppliers in recommendations provided to users. This is especially important in multistakeholder recommendation scenarios where it may be important to optimize utilities not just for the end user but also for other stakeholders such as item sellers or producers who desire a fair representation of their items. This type of supplier fairness is sometimes accomplished by attempting to increase aggregate diversity to mitigate popularity bias and to improve the coverage of long-tail items in recommendations. In this article, we introduce FairMatch, a general graph-based algorithm that works as a post-processing approach after recommendation generation to improve exposure fairness for items and suppliers. The algorithm iteratively adds high-quality items that have low visibility or items from suppliers with low exposure to the users' final recommendation lists. A comprehensive set of experiments on two datasets and comparison with state-of-the-art baselines show that FairMatch, although it significantly improves exposure fairness and aggregate diversity, maintains an acceptable level of relevance of the recommendations.

CCS Concepts: • **Information systems** → **Personalization**; **Information retrieval diversity**; **Recommender systems;**

Additional Key Words and Phrases: Recommender systems, exposure fairness, popularity bias, long-tail, aggregate diversity

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1 INTRODUCTION

Recommender systems use historical data on interactions between users and items to generate personalized recommendations for the users. These systems are used in a variety of different applications, including movies, music, e-commerce, online dating, and many other areas where the number of options from which the user needs to choose can be overwhelming. There are many different metrics to evaluate the performance of the recommender systems, ranging from accuracy metrics such as precision, normalized discounted cumulative gain (NDCG), and recall to non-accuracy ones like novelty and serendipity [11, 23, 44].

All these metrics mentioned previously are usually calculated using each individual recommendation list to a given user. However, there are certain aspects of the recommendations that need to be looked at in a more holistic way across all users. For example, how successful a given recommender system is in giving enough chance to different items to be seen by different users cannot be measured by looking at individual recommendations separately. This is particularly important in domains where fairness of the recommendations can be critical for the success of the recommendation platform, such as job recommendation, philanthropy, and online dating.

One of the main reasons for different items not getting fair exposure in the recommendations is the popularity bias problem where few popular items are over-recommended while the majority of other items do not get deserved attention. For example, in a music recommendation system, few popular artists might take up the majority of the streamings leading to under-exposure of less popular artists. This bias, if not mitigated, can negatively affect the experience of different users and items on the platform [4, 32]. It could also be perpetuated over time by the interaction of users with biased recommendations and, as a result, using biased interactions for training the model in the subsequent times [12, 14, 30, 41, 43].

There are numerous methods to tackle this popularity bias by either modifying the underlying recommendation algorithms by incorporating the popularity of each item [2, 6, 43, 45] or as a post-processing reranking step to modify an existing, often larger, recommendation list and extract a shorter list that has a better characteristics in terms of fair exposure of different items [3, 7–9]. However, most of these of algorithms solely concentrated on mitigating the exposure (visibility) bias in an item level. What these algorithms ignore is the complexity of many real-world recommender systems where there are different suppliers that provide the recommended items and hence the fairness of exposure in a supplier level needs to also be addressed [1]. One way to improve supplier exposure fairness is to improve the visibility of items, hoping it will also lead to giving a more balanced exposure to different suppliers as often there is a positive correlation between the popularity of suppliers and their items. However, only optimizing for item visibility without explicitly taking into account the suppliers in the recommendations does not necessarily make the recommendations fairer for suppliers, as we explain in Section 3.

In this article, we introduce *FairMatch*, a general graph-based algorithm that works as a post-processing approach after recommendation generation (on top of any existing standard recommendation algorithm). The idea is to generate a list of recommendations with a size larger than what we ultimately want for the final list using a standard recommendation algorithm and then use our FairMatch algorithm to build the final list using a subset of items in the original list. This is done by iteratively solving the *maximum flow* problem on a recommendation bipartite graph that is built using the recommendations in the original list (left nodes are recommended items and right nodes are the users). At each iteration, the items that can be good candidates for the final list will be selected and removed from the graph and the process will continue on the remaining part of the graph. FairMatch is able to systematically improve the visibility of different items and suppliers in the recommendations while maintaining an acceptable level of relevance to the users.

This work is an extension of our previously proposed algorithm that was only capable of improving item visibility [29]. This extended version, however, is able to improve the visibility of items or suppliers of the items depending on which one we pick as our optimization criterion.

To show the effectiveness of our FairMatch algorithm on improving aggregate diversity and fair visibility of recommended items and suppliers, we perform a comprehensive set of experiments using three standard recommendation algorithms as the base for our reranking method. Comparison with several state-of-the-art baselines shows that our FairMatch algorithm is able to significantly improve the performance of recommendation results in terms of visibility of different items and suppliers with a negligible loss in the recommendation accuracy in some cases.

In summary, we make the following contributions:

- We propose a graph-based approach for improving the exposure fairness of items and suppliers in the recommendations.
- We propose several metrics that can better measure the effectiveness of an algorithm in mitigating the exposure bias for items and suppliers.
- We compare our proposed algorithm with several state-of-the-art methods in mitigating popularity and exposure bias and show the effectiveness of our algorithm in doing so.

2 RELATED WORK

Research on fairness and algorithmic bias have revealed that there are different types of bias in recommendation systems that, if not mitigated, can negatively affect the system [13]. Various algorithmic solutions have been proposed to address this issue. For example, Yao and Huang [46] improved the fairness of recommendation results by adding fairness terms to objective function in model-based recommendation algorithms. As another example, Liu et al. [28] proposed a reinforcement learning based framework to address the trade-off between accuracy and fairness in interactive recommender systems. These works mainly addressed group fairness when users are grouped based on a sensitive attribute. There are also studies addressing other types of bias such as position bias [10]. However, this article focuses on exposure bias in recommendation results. In this section, we review the literature on exposure bias in recommender systems.

The concept of popularity bias has been studied by many researchers often under different names such as long-tail recommendation [2, 47], Matthew effect [33], and aggregate diversity [7, 27] all of which refer to the fact that the recommender system should recommend a wider variety of items across all users.

The solutions for tackling popularity bias in the literature can be categorized into two groups[1]: *model based* [2, 6, 43, 45] and *reranking* [3, 7–9]. In model-based solutions, the recommendation generation step is modified so that the popularity of the items is taken into account in the rating prediction. For example, Abdollahpouri et al. [2] proposed a regularization term to control the popularity of recommended items that could be added to an existing objective function of a learning-to-rank algorithm [24] to improve the aggregate diversity of the recommendations. In another work, Vargas and Castells [44] proposed probabilistic models for improving novelty and diversity of recommendations by taking into account both relevance and novelty of target items when generating recommendation lists. Moreover, Vargas and Castells [45] proposed the idea of recommending users to items for improving novelty and aggregate diversity. They applied this idea to nearest neighbor models as an inverted neighbor and a factorization model as a probabilistic reformulation that isolates the popularity components.

[1] A third option, pre-processing, is generally not useful for popularity bias mitigation because undersampling the popular items greatly increases the sparsity of the data.

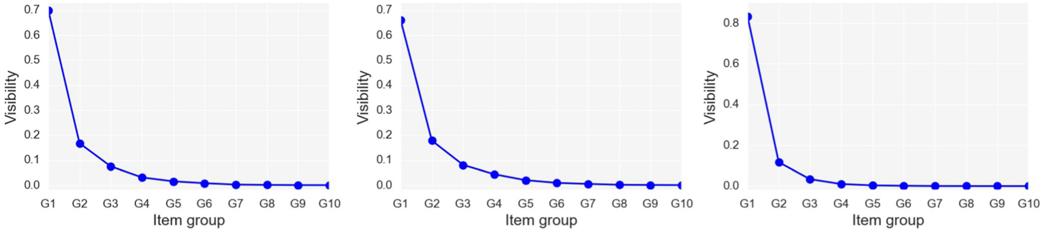
In the second approach for improving aggregate diversity, the algorithm takes a larger output recommendation list and reorders the items in the list to extract a shorter final list with improved long-tail properties. Most of the solutions for tackling popularity bias fall into this category. For example, Adomavicius and Kwon [8] proposed the idea of diversity maximization using a maximum flow approach. They used a specific setting for the bipartite recommendation graph in a way that the maximum amount of flow that can be sent from a source node to a sink node would be equal to the maximum aggregate diversity for those recommendation lists. In their setting, given the number of users is m, the source node can send a flow of up to m to the left nodes, left nodes can send a flow of up to 1 to the right nodes, and right nodes can send a flow of up to 1 to the sink node. Since the capacity of left nodes to right nodes is set to 1, thus the maximum possible amount of flow through that recommendation bipartite graph would be equivalent to the maximum aggregate diversity.

A more recent graph-based approach for improving aggregate diversity that also falls into the reranking category was proposed by Antikacioglu and Ravi [9]. They generalized the idea proposed by Adomavicius and Kwon [8] and showed that the minimum-cost network flow method can be efficiently used for finding recommendation subgraphs that optimizes the diversity. In this work, an integer-valued constraint and an objective function are introduced for discrepancy minimization. The constraint defines the maximum number of times that each item should appear in the recommendation lists and the objective function aims to find an optimal subgraph that gives the minimum discrepancy from the constraint. This work shows improvement in aggregate diversity of the items with a smaller accuracy loss compared to the work of Vargas and Castells [44, 45]. Our algorithm is also a graph-based approach that not only is it able to improve aggregate diversity and the exposure fairness of items but also gives the suppliers of the recommended items a fairer chance to be seen by different users. Moreover, unlike the work of Antikacioglu and Ravi [9] that tries to minimize the discrepancy between the distribution of the recommended items and a target distribution, our FairMatch algorithm has more freedom in promoting high-quality items or suppliers with low visibility since it does not assume any target distribution of the recommendation frequency.

Another work that also uses a reranking approach is by Abdollahpouri et al. [3], where the authors proposed a diversification method for improving aggregate diversity and long-tail coverage in recommender systems. Their method was based on the *eXplicit Query Aspect Diversification* (xQuAD) algorithm [38] that was designed for diversifying the query result such that it covers different aspects related to a given query. Abdollahpouri et al. [3] used the xQuAD algorithm for balancing the ratio of popular and less popular (long-tail) items in final recommendation lists.

In addition, in an earlier work [29], we proposed a graph-based algorithm that finds high-quality items that have low visibility in the recommendation lists by iteratively solving the maximum flow problem on recommendation bipartite graph. The present work extends the idea of Mansoury et al. [29] for improving the exposure fairness of items and suppliers. We also discuss the limitations of existing metrics for measuring the exposure bias in recommendation results and propose several metrics to overcome those limitations.

In addressing exposure bias in domains like job recommendations where job seekers or qualified candidates are recommended, Zehlike et al. [48] proposed a reranking algorithm to improve the ranked group fairness in recommendations. The algorithm creates queues of protected and unprotected items and merges them using normalized scoring such that protected items get more exposure. Singh and Joachims [40] discussed how exposure bias can lead to unfair treatment of different groups of users in ranking systems. They proposed a general framework for addressing the exposure bias when maximizing the utility for users in generating the ranked results. Geyik et al. [18] explored the exposure bias in LinkedIn Talent Search where the distribution of applicants



(a) BPR (b) NCF (c) UserKNN

Fig. 1. Visibility of recommended items for different recommendation algorithms on the MovieLens dataset.

belonging to different groups of sensitive attributes in recommendation lists do not follow the distribution of applicants' group in the initial search results. They showed that applicants belong to the protected group are often under-recommended. To address this issue, the authors proposed an algorithm to achieve the desired distribution of applicants' group with respect to sensitive attributes in top-n recommendation results.

Most of the existing works in the literature for improving aggregate diversity and exposure fairness have only concentrated on the items and ignored the fact that in many recommendation domains the recommended items are often provided by different suppliers, and hence their utility should also be investigated. To the best of our knowledge, there are only few prior works that have addressed this issue (e.g., [5, 32]. Abdollahpouri et al. [5] illustrated how popularity bias is a multistakeholder problem, and hence they evaluated their solution for mitigating this bias from the perspective of different stakeholders. Mehrotra et al. [32] investigated the trade-off between the relevance of recommendations for users and supplier fairness, and their impacts on users' satisfaction. Relevance of the recommended items to a user is determined by the score predicted by a recommendation algorithm. To determine the supplier fairness in a recommendation list, first suppliers are grouped into several bins based on their popularity in rating data and then the supplier fairness of a recommendation list is measured as how diverse the list is in terms of covering different supplier popularity bins.

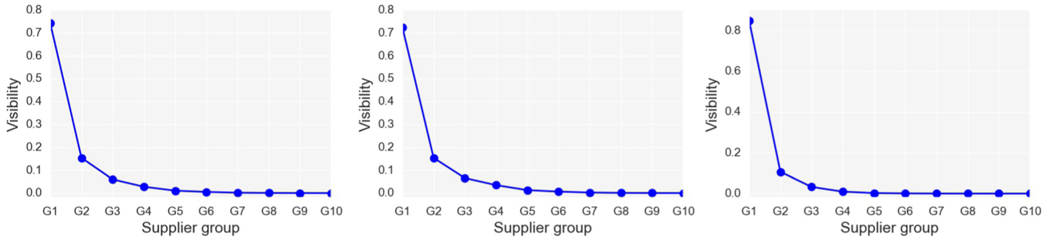
Our work in this article also observes the importance of evaluating algorithms from the perspective of multiple stakeholders, and we propose an algorithm that can directly improve the visibility of the suppliers without losing much accuracy from the users' perspective.

3 EXPOSURE BIAS IN RECOMMENDATION

It is well known that recommendation algorithms favor popular items, which leads to an unfair exposure of other items that might not be as popular [2, 42]. This bias toward popular items can negatively affect the less popular items, items that are new to the system (a.k.a. cold start items), and even the supplier of the items [1, 34]. In this section, we illustrate the exposure bias of several recommendation algorithms from both the item and supplier perspective. The mathematical and formulated definitions of exposure for items or suppliers are presented in Section 5.4.

3.1 Bias in Item Exposure

An exposure for an item is the percentage of the times it has appeared in the recommendations [25, 40]. Recommendation algorithms are often biased toward more popular items giving them more exposure than many other items. Figure 1 shows the visibility of different items in the recommendations produced by three recommendation algorithms: **Bayesian Personalized Ranking** (BPR) [35], **Neural Collaborative Filtering** (NCF) [22], and **User-based Collaborative Filtering** (UserKNN) [36]. Items are binned into 10 equal-size groups based on their visibility in



(a) BPR (b) NCF (c) UserKNN

Fig. 2. Visibility of suppliers for different recommendation algorithms on the MovieLens dataset.

recommendation lists such that each bin contains the same number of items. In other words, items are first sorted based on their visibility in recommendation lists and then 10 equal-size groups of items are created. We can see that in all three algorithms, there is a long-tail shape for the visibility of the items indicating that few popular item groups are recommended much more frequently than the others creating an item exposure bias in the recommendations. Not every algorithm has the same level of exposure bias for different items. For instance, we can see that UserKNN has recommended items from group G_1 to roughly 80% of the users, whereas this number is near 70% and 65% for BPR and NCF, respectively. However, G_2 has received less exposure in UserKNN (10%) compared to BPR and NCF, which have given 17% and 19% visibility to items in this group, respectively.

3.2 Bias in Supplier Exposure

The unfair exposure does not only affect the items in a recommender system. We know that in many recommendation platforms, the items to be recommended are provided by different suppliers. Therefore, the dynamic of how recommendation algorithms can impact the experience of the suppliers is also crucial. Abdollahpouri and Mansoury [4] empirically show that recommendation algorithms often over-promote items from popular suppliers while suppressing the less popular ones. Figure 2 shows a similar plot to Figure 1 but for the suppliers of the items. Similar to items, suppliers are binned into 10 groups based on their visibility in recommendation lists. The same problem that we observed in Figure 1 also exists here: in all three algorithms, there is a long-tail shape for the visibility of the suppliers indicating that few supplier groups are recommended much more frequently than the others.

There are many existing works for improving the visibility of different items in the recommendations and reducing the exposure bias in items. However, the same cannot be said about the suppliers, and there has not been much attention to improving the supplier visibility/exposure. Although improving the item visibility can, indirectly, help suppliers as well as it was demonstrated in the work of Abdollahpouri et al. [5], a more explicit incorporation of suppliers in the recommendation process can yield fairer outcomes for different suppliers in terms of visibility.

Our work in this article aims to address this problem by directly incorporating the suppliers in the recommendation process to mitigate the exposure bias from the supplier perspective.

3.3 Motivating Example

Figure 3 shows a scenario where we have a list of items as the candidate pool, and the goal is to extract a list of recommendations (in this example, the size is 3 for illustration purposes) and recommend it to the user. In addition, items are categorized to either *high visibility* (i.e., frequently recommended) and *low visibility* (less frequently recommended). Moreover, each item is also provided by either supplier A or B. Three recommendation algorithms (these are just for illustration purposes) are compared in terms of how they extract the final list of three items. The first

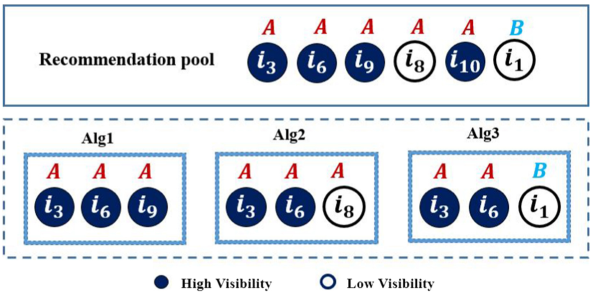


Fig. 3. Comparison between a relevance-based recommendation algorithm (*Alg*1), item visibility-aware reranker (*Alg*2), and supplier visibility-aware reranker (*Alg*3).

algorithm, *Alg1*, extracts the three most relevant items from the top of the list without considering the visibility of items or which supplier they belong to. Obviously, this algorithm performs poorly in terms the fairness of item exposure and supplier exposure since only highly relevant items are recommended and they are all from supplier *A*. In contrast, the second algorithm, *Alg2*, extracts the final recommendation list by also taking into account the visibility of items. This algorithm could represent many existing approaches to overcome exposure bias in recommendation. However, although the list of recommended items is now more diverse in terms of different type of items (high visibility vs. low visibility), it still only contains items from supplier *A* since the supplier information was not incorporated in the algorithm. The third algorithm, *Alg3*, however, has recommended a diverse list of items not only in terms of items but also in terms of the suppliers of those items. This is the type of algorithm we intend to develop in this work.

In the next section, we present our algorithm, FairMatch, which can systematically improve the exposure of less popular items and suppliers while maintaining an acceptable level of relevance to the users.

4 THE FAIRMATCH ALGORITHM

We formulate our FairMatch algorithm as a post-processing step after the recommendation generation. In other words, we first generate recommendation lists of larger size than what we ultimately desire for each user using any standard recommendation algorithm and use them to build the final recommendation lists. FairMatch works as a batch process, similar to that proposed by Sürer et al. [49] where all the recommendation lists are produced at once and reranked simultaneously to achieve the objective. In this formulation, we produce a longer recommendation list of size t for each user, and then, after identifying candidate items (based on defined utility, more details in Section 4.2) by iteratively solving the maximum flow problem on a recommendation bipartite graph, we generate a shorter recommendation list of size n (where $t >> n$).

Let $G = (I, U, E)$ be a bipartite graph of recommendation lists where I is the set of left nodes, U is the set of right nodes, and E is the set of edges between left and right nodes when recommendation occurred. G is initially a uniformly weighted graph, but we will update the weights for edges as part of our algorithm. We will discuss the initialization and our weighting method in Section 4.2.

Given a weighted bipartite graph G, the goal of our FairMatch algorithm is to improve the exposure fairness of recommendations without a significant loss in accuracy of the recommendations. We define exposure fairness as providing equal chance for items or suppliers to appear in recommendation lists. The FairMatch algorithm does this by identifying items or suppliers with low visibility in recommendation lists and promotes them in the final recommendation lists while maintaining the relevance of recommended items for users. We develop our algorithm by extending the

ALGORITHM 1: The FairMatch Algorithm

```
function FairMatch(Recommendations $R$, TopN $n$, Suppliers $S$, Coefficient $\lambda$)
    Build graph $G = (I, U, E)$ from $R$
    Initialize subgraphs to empty
    repeat
        $G$ = WeightComputation($G$, $R$, $S$, $\lambda$)
        $\mathcal{I}_C$ = Push-relabel($G$)
        Initialize subgraph to empty
        for each $i \in \mathcal{I}_C$ do
            if $label_i \geq |I| + |U| + 2$ then
                for each $u \in Neighbors(i)$ do
                    Append $< i, u, e_{iu} >$ to subgraph
                end for
            end if
        end for
        if subgraph is empty then
            break
        end if
        Append subgraph to subgraphs
        $G$ = Remove subgraph from $G$
    until (true)
    Reconstruct $R$ of size $n$ based on subgraphs
end function
```

approach introduced in the work of Garcia-Soriano and Bonchi [17] to improve the exposure fairness of the recommender systems.

We use an iterative process to identify the subgraphs of G that satisfy the underlying definitions of fairness without a significant loss in accuracy of the recommendation for each user. After identifying a subgraph Γ at each iteration, we remove Γ from G and continue the process of finding subgraphs on the rest of the graph (i.e., G/Γ). We keep track of all the subgraphs as we use them to generate the final recommendations in the last step.

Identifying Γ at each iteration is done by solving a *maximum flow* problem (explained in Section 4.3) on the graph obtained from the previous iteration. Solving the maximum flow problem returns the left nodes connected to the edges with lower weight on the graph. After finding those left nodes, we form subgraph Γ by separating identified left nodes and their connected right nodes from G. Finally, $< user, item >$ pairs in subgraphs are used to construct the final recommendation lists of size n. We will discuss this process in detail in the following sections.

Algorithm 1 shows the pseudocode for FairMatch. Overall, our FairMatch algorithm consists of the following four steps: (1) graph preparation, (2) weight computation, (3) candidate selection, and (4) recommendation list construction. Figure 4 shows the process of the FairMatch algorithm. FairMatch takes the long recommendation lists of size t generated by a base recommendation algorithm as input, and then over four consecutive steps, as mentioned earlier, it generates the final recommendation lists. The details about each step in FairMatch algorithm will be discussed in the following sections.

4.1 Graph Preparation

Given long recommendation lists of size t generated by a standard recommendation algorithm, we create a bipartite graph from recommendation lists in which items and users are the nodes and recommendations are expressed as edges. Since our FairMatch algorithm is formulated as a

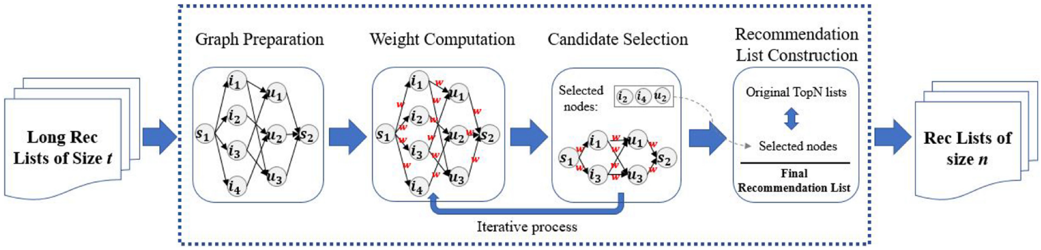


Fig. 4. The process of the FairMatch algorithm.

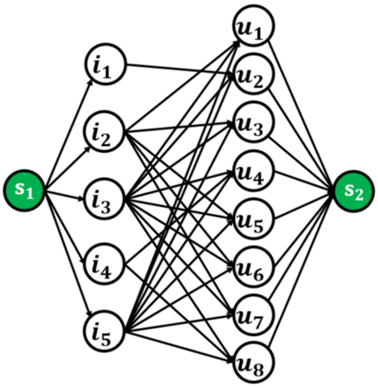


Fig. 5. An example of a recommendation bipartite graph of recommendation lists of size 3.

maximum flow problem, we also add two nodes: *source* (s_1) and *sink* (s_2). The purpose of having a source and sink node in the maximum flow problem is to have a start and endpoint for the flow going through the graph. We connect s_1 node to all left nodes and also connect all right nodes to s_2. Figure 5 shows a sample bipartite graph resulted in this step.

4.2 Weight Computation

The weight computation step plays an important role in improving the exposure fairness of recommendations in the proposed model. Depending on the fairness definition that we desire to achieve, the weight computation step should be adapted accordingly. In this section, we discuss how weight computation can be adapted for improving the exposure fairness of items or suppliers.

Given the bipartite recommendation graph, $G = (I, U, E)$, the task of weight computation is to calculate the weight for edges between the source node and left nodes, left nodes and right nodes, and right nodes and sink node.

For edges between left nodes and right nodes, we define the weights as the weighted sum of user utility and supplier utility (or instead, item utility). The utility of each user is defined as the relevance of recommended items for that user. Given the long recommendation list of size t for user u as L_u, in our formulation, we define the relevance of an item i for user u as rank of i in sorted L_u in descending order based on predicted score by the base recommender. This way, items in lower rank will be more relevant to the user (e.g., the item in the first rank is the most relevant one).

The utility for each item and supplier is defined as their exposure or visibility in the long recommendation lists. The visibility of each item is defined as the degree of the node corresponding to that item (excluding the edge with the source node). Item degree is the number of edges going out from that node connecting it to the user nodes and that shows how often it is recommended to different users. Analogously, the visibility for each supplier is defined as the sum of the degree of all nodes corresponding to the items belonging to that supplier. Therefore, we introduce two separate weight computation schemes, one for item utility and another for supplier utility, which eventually results in two variations of FairMatch algorithm as follows:

- $FairMatch^{item}$**:** For computing the weight for edges between $i \in I$ and $u \in U$, we use the following equation:

$$w_{iu} = \lambda \times rank_{iu} + (1-\lambda) \times degree_i, \tag{1}$$

where $rank_{iu}$ is the position of item i in the sorted recommendation list of size t generated for user u, $degree_i$ is the number of edges from i to right nodes (i.e., $u \in U$), and λ is a coefficient to control the trade-off between the relevance of the recommendations and the exposure of items.
- $FairMatch^{Sup}$**:** For computing the weight for edges between $i \in I$ and $u \in U$, we use the following equation:

$$w_{iu} = \lambda \times rank_{iu} + (1-\lambda) \times \sum_{i \in A(B(i))} degree_i \tag{2}$$

where $B(i)$ returns the supplier of item i and $A(B(i))$ returns all items belonging to the supplier of item i. Therefore, the term $\sum_{i \in A(B(i))} degree_i$ computes the visibility of supplier of item i (i.e., the sum of visibility of all items that belong to the supplier of item i). $rank_{iu}$ and λ have the same definition as Equation (1).

Note that in Equations (1) and (2), $rank_{iu}$ and visibility for suppliers and items have different ranges. The range for $rank_{iu}$ is from 1 to t (there are t different positions in the original list), and the range of visibility depends on the frequency of the item (or its supplier) recommended to the users (the more frequently it is recommended to different users the higher its degree is). Hence, for a meaningful weighted sum, we normalize visibility of items and suppliers to be in the same range as $rank_{iu}$.

Given weights of the edges between $i \in I$ and $u \in U$, w_{iu}, the total capacity of I and U would be $C_T = \sum_{i \in I} \sum_{u \in U} w_{iu}$, which simply shows the sum of the weights of the edges connecting left nodes to the right nodes.

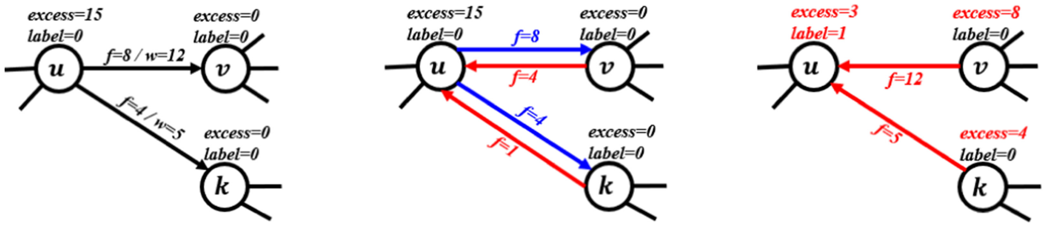
For computing the weight for edges connected to the source and sink nodes, first we equally distribute C_T to left and right nodes. Therefore, the capacity of each left node, $C_{eq}(I)$, and right node, $C_{eq}(U)$, would be as follows:

$$C_{eq}(I) = \left\lceil \frac{C_T}{|I|} \right\rceil, \qquad C_{eq}(U) = \left\lceil \frac{C_T}{|U|} \right\rceil, \tag{3}$$

where $\lceil a \rceil$ returns the ceil value of a. Then, based on equal capacity assigned to each left and right nodes, we follow the method introduced in the work of Garcia-Soriano and Bonchi [17] to compute weights for edges connected to source and sink nodes as follows:

$$\forall i \in I, w_{s_1 i} = \left\lceil min\left(\frac{C_{eq}(I)}{gcd(C_{eq}(I), C_{eq}(U))}, \frac{C_{eq}(U)}{gcd(C_{eq}(I), C_{eq}(U))}\right)\right\rceil, \tag{4}$$

$$\forall u \in U, w_{us_2} = \left\lceil \frac{C_{eq}(I)}{gcd(C_{eq}(I), C_{eq}(U))} \right\rceil, \tag{5}$$



(a) Original graph (b) Residual graph (c) Pushing excess flow of u

Fig. 6. Example of push and relabel operations.

where $gcd(C_{eq}(I), C_{eq}(U))$ is the Greatest Common Divisor of the distributed capacity of left and right nodes. Assigning the same weight to edges connected to the source and sink nodes guarantees that all nodes in I and U are treated equally and the weights between them play an important role in our FairMatch algorithm.

4.3 Candidate Selection

The graph constructed in previous steps is ready to be used for solving the maximum flow problem. In a maximum flow problem, the main goal is to find the maximum amount of feasible flow that can be sent from the source node to the sink node through the flow network. Several algorithms have been proposed for solving a maximum flow problem. Well-known algorithms are Ford–Fulkerson [16], push-relabel [19], and Dinic's algorithm [15]. In this work, we use the push-relabel algorithm to solve the maximum flow problem on our bipartite recommendation graph as it is one of the efficient algorithms for this matter and also it provides some functionalities that our FairMatch algorithm benefits them.

In the push-relabel algorithm, each node will be assigned two attributes: *label* and *excess flow*. The label attribute is an integer value that is used to identify the neighbors to which the current node can send flow. A node can only send flow to neighbors that have lower label than the current node. Excess flow is the remaining flow of a node that can still be sent to the neighbors. When all nodes of the graph have excess flow equal to zero, the algorithm will terminate.

The push-relabel algorithm combines *push* operations that send a specific amount of flow to a neighbor and *relabel* operations that change the label of a node under a certain condition (when the node has excess flow greater than zero and there is no neighbor with a label lower than the label of this node).

Here is how the push-relabel algorithm works. Figure 6 shows a typical graph in the maximum flow problem and an example of push and relabel operations. In Figure 6(a), f and w are the current flow and weight of the given edge, respectively. In the push-relabel algorithm, a residual graph, $G^{'}$, will be also created from graph G. As graph G shows the flow of forward edges, graph $G^{'}$ shows the flow of backward edges calculated as $f_{backward} = w - f$. Figure 6(b) shows a residual graph of graph G in Figure 6(a). Now, we want to perform a push operation on node u and send its excess flow to its neighbors.

Given x_u as excess flow of node u, the $push(u, v)$ operation will send a flow of amount $\Delta = min(x_u, f_{uv})$ from node u to node v and then will decrease excess flow of u by Δ (i.e., $x_u = x_u - \Delta$) and will increase excess flow of v by Δ (i.e., $x_v = x_v + \Delta$). After the $push(u, v)$ operation, node v will be put in a queue of active nodes to be considered by the push-relabel algorithm in the next iterations and the residual graph would be updated. Figure 6(c) shows the result of $push(u, v)$ and $push(u, k)$ on the graph shown in Figure 6(b). In $push(u, v)$, for instance, since u and all of its neighbors have the same label value, to perform the push operation, first we need to perform the relabel operation on node u to increase the label of u by one unit more than the minimum label of its neighbors to guarantee that there is at least one neighbor with a lower label for performing the push operation. After that, node u can send flow to its neighbors.

Given $x_u = 15$, $f_{uv} = 8$, and $f_{uk} = 4$ in Figure 6(b), after performing the relabel operation, we can only send the flow of amount 8 from u to v and the flow of amount 4 from u to k. After these operations, the residual graph (backward flow from v and k to u) will be updated.

The push-relabel algorithm starts with a "preflow"operation to initialize the variables and then it iteratively performs push or relabel operations until no active node exists for performing operations. Assuming $\mathcal{L}_v$ as the label of node v, in the preflow step, we initialize all nodes as follows: $\mathcal{L}_{s_1} = |I|+|U|+2$, $\mathcal{L}_{i\in I} = 2$, $\mathcal{L}_{u\in U} = 1$, and $\mathcal{L}_{s_2} = 0$. This way, we will be able to send the flow from s_1 to s_2 as the left nodes have a higher label than the right nodes. In addition, we will push the flow of amount $w_{s_1 i}$ (where $i \in I$) from s_1 to all the left nodes. After preflow, all of the left nodes $i \in I$ will be in the queue, Q, as active nodes because all those nodes now have positive excess flow. The main part of the algorithm will now start by dequeuing an active node v from Q and performing either push or relabel operations on v as explained earlier. This process will continue until Q is empty. At the end, each node will have specific label value and the sum of all the coming flows to node s_2 would be the maximum flow of graph G. For more details, see the work of Goldberg and Tarjan [19].[2]

An important question is this: *how does the push-relabel algorithm find high-quality (more relevant) nodes (items and their suppliers) with low degree (visibility)?* We answer this question by referring to the example in Figure 6(c). In this figure, assume that u has a backward edge to s_1. Since u has excess flow greater than zero, it should send it to its neighbors. However, as you can see in the figure, u does not have any forward edge to v or k nodes. Therefore, it has to send its excess flow back to s_1 as s_1 is the only reachable neighbor for u. Since s_1 has the highest label in our setting, for u to push all its excess flow back to s_1, it should go through a relabel operation so that its label becomes larger than that of s_1. Therefore, the label of u will be set to $\mathcal{L}_{s_1} + 1$ for an admissible push.

The reason that u receives high label value is the fact that it initially receives high flow from s_1 (it is important how to assign weight to edges between s_1 and left nodes), but it does not have enough capacity (the sum of weights between u and its neighbors is smaller than its excess flow, i.e., $8 + 4 < 15$) to send all that flow to them.

In FairMatch, in step 2 (i.e., Section 4.2), the same weight is assigned to all edges connected to s_1 and s_2. This means that the capacity of edges from s_1 to all item nodes would be the same and also the capacity of edges from all user nodes to s_2 would be the same. However, the weights assigned to edges between item and user nodes depend on the quality and visibility of the recommended items to users in the recommendation lists and play an important role in finding the desired output in the FairMatch algorithm. Assume that the weights for edges between s_1 and item nodes are w_{s_1} and the weights for edges between user nodes and s_2 are w_{s_2}.

In the preflow step, s_1 sends flow of amount w_{s_1} to each item node in I and this flow would be recorded in each of the item nodes as their excess flow. When push-relabel starts after preflow, the algorithm tries as much as possible to send the excess flow in item nodes to user nodes and then finally to s_2. However, the possibility of achieving this objective depends on the capacity of edges between item and user nodes. Items connected to edges with low capacity will not be able to send all their excess flow to their neighbors (user nodes) and will be returned as candidate items in step 3 of the FairMatch algorithm.

[2] You can interactively run the push-relabel algorithm on your graph here: http://www.adrian-haarbach.de/idp-graph-algorithms/implementation/maxflow-push-relabel/index_en.html.

There are two possible reasons for some items to not be able to send all their excess flow to their neighbors. First, they have few neighbors (user nodes), which signifies that those items are recommended to few users and consequently they have low visibility in recommendation lists. Second, they are relevant to the users' preferences, meaning that their rank in the recommendation list (sorted based on the predicted score by a base recommender) for users is low and consequently make those items more relevant to users. Hence, these two reasons—low visibility and high relevance—cause some items to not have sufficient capacity to send their excess flow to their neighbors (user nodes) and have to send it back to s_1 similar to what we illustrated earlier. As a result, sending back the excess flow to s_1 means first running the relabel operation as s_1 has a higher label value than item nodes and then push the excess flow to s_1. Performing the relabel operation will assign the highest label value to those items, which makes them be distinguishable from other nodes after the push-relabel algorithm terminated. Therefore, in step 3 (i.e., Section 4.3), left nodes without sufficient capacity on their edges will be returned as part of the outputs from the push-relabel algorithm and are considered for constructing the final recommendation list in step 4 (i.e., Section 4.4). FairMatch aims at promoting those high-relevance items (or suppliers) with low visibility.

4.4 Recommendation List Construction

In this step, the goal is to construct a recommendation list of size n by the $< user, item >$ pairs identified in the previous step. Given a recommendation list of size n for user u, L_u, sorted based on the scores generated by a base recommendation algorithm, candidate items identified by FairMatch connected to u as $\mathcal{I}_C$, and visibility of each item i in recommendation lists of size n as $\mathcal{V}_i$, we use the following process for generating recommendation list for u. First, we sort recommended items in L_u and $\mathcal{I}_C$ based on their $\mathcal{V}_i$ in ascending order. Then, we remove $min(\beta \times n, |\mathcal{I}_C|)$ from the bottom of sorted L_u and add $min(\beta \times n, |\mathcal{I}_C|)$ items from $\mathcal{I}_C$ to the end of L_u. β is a hyperparameter in $0 < \beta \leq 1$ that specifies the fraction of items in the original recommendation lists that we want to replace with the identified items in the previous step.

This process will ensure that extracted items in the previous step will replace the frequently recommended items, meaning that it decreases the visibility of the frequently recommended items/suppliers and increases the visibility of rarely recommended items/suppliers to generate a fairer distribution on recommended items/suppliers.

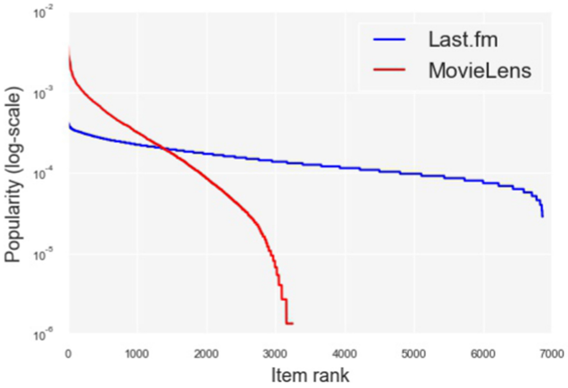
5 EXPERIMENTAL METHODOLOGY

We performed a comprehensive evaluation of the effectiveness of the FairMatch algorithm in improving the exposure fairness of recommender systems. Our evaluation on three standard recommendation algorithms and comparison to various bias mitigation methods as baselines on two publicly available datasets shows that the FairMatch algorithm significantly improves the exposure fairness of the recommendations with a relatively small loss in the accuracy of recommendations.

5.1 Data

Experiments are performed on two publicly available datasets: Last.fm[3] [39] and MovieLens [21]. The Last.fm dataset contains user interactions with songs (and the corresponding albums). We used the same methodology as that in the work of Kowald et al. [26] to turn the interaction data into rating data using the frequency of the interactions with each item (more interactions with an item will result in a higher rating). In addition, we used albums as the items to reduce the size and sparsity of the item dimension, and therefore the recommendation task is to recommend albums

[3] http://www.cp.jku.at/datasets/LFM-1b/.



(a) Last.fm

Fig. 7. Item popularity in Last.fm and MovieLens datasets.

to users. We considered the artists associated with each album as the supplier of that album. After pre-processing the data,[4] there are 2,000 users who provided 218,985 ratings on 6,817 albums. In addition, there are 2,856 suppliers (i.e., artists) in this dataset.

The MovieLens dataset is a movie rating data and was collected by the GroupLens[5] research group. We considered the movie-maker associated with each movie as the supplier of that movie. Since this dataset does not originally contain information about the movie-makers, we used the API provided by the OMDB (not to be confused with IMDB) website[6] to extract the information about movie-makers associated with different movies. Overall, there are 6,040 users who provided 928,739 ratings on 3,079 movies, and there are 1,699 suppliers (i.e., movie-makers) in this dataset.

These datasets are from different domains, have different levels of sparsity, and are different in terms of popularity distribution of different items. Figure 7 shows the distribution of item popularity in both datasets. For readability, we used log-scale for the y-axis. We can see that MovieLens shows a much more extreme long-tail shape than Last.fm, indicating that there is more inequality in terms of the number of times each item is rated. In Last.fm, generally the distribution seems to be fairer for different items, which means that there is less bias in data and therefore less bias will be in the recommendations. That, however, also means that the reranking algorithms will have a harder time improving the visibility of different items (as we will see in Table 1 and Figures 11(a) and 12(a)) since the base algorithm already does a relatively good job in doing so.

It is also worth noting that different suppliers do not own the same number of items, as we can see in Figure 8, where the majority of suppliers have only one item. Because of this, we will see that both versions of our FairMatch algorithm perform relatively similar in some cases since improving item visibility for those items that belong to suppliers with only one item is indeed equivalent to improving the visibility of the corresponding supplier.

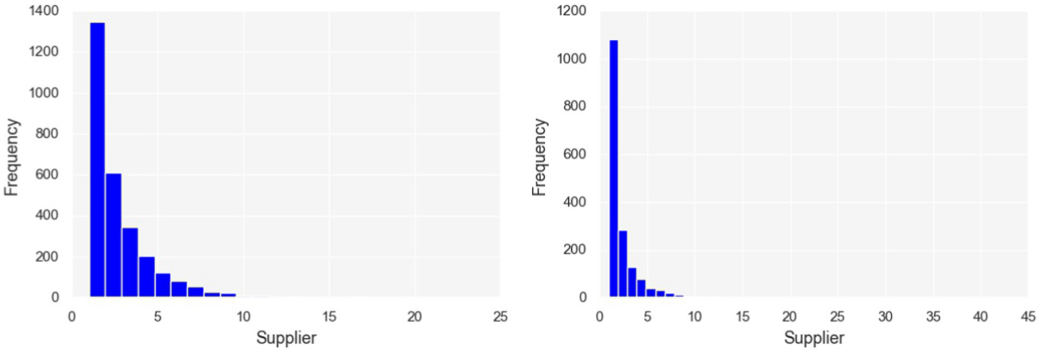
5.2 Setup

We used 80% of each dataset as our training set and the other 20% for the test. The training set was used for building a recommendation model and generating recommendation lists, and the test set was used for evaluating the performance of generated recommendations. We generated recommendation lists of size $t = 50$ for each user using each recommendation algorithm. We

[4] We removed users with less than 50 ratings and items with less than 200 ratings to create a denser dataset and then randomly sampled 2,000 users from the data.

[5] https://grouplens.org/datasets/movielens/.

[6] http://www.omdbapi.com/.



(a) Last.fm (b) MovieLens

Fig. 8. Histogram of supplier inventory (the number of items each supplier owns).

then extracted the final recommendation lists of size $n = 10$ using each reranking method by processing the recommendation lists of size 50. We also performed experiments with $t = 100$ and $n \in \{5, 15, 20\}$, but in this work we only report the results for $t = 50$ and $n = 10$ as we observed the same patterns in all experiments. We used *librec-auto* and LibRec 2.0 for running the experiments [20, 31].

The initial longer recommendation lists of size $t = 50$ are generated by three well-known recommendation algorithms: `BPR` [35], `NCF` [22], and `UserKNN` [36]. We chose these algorithms to cover different approaches in recommender systems: matrix factorization, neural networks, and neighborhood models. We performed gridsearch[7] on hyperparameters for each algorithm and selected the results with the highest precision value for our next analysis. We used McNemar's test to evaluate the significance of results, and based on McNemar's test, the results shown with an underline in Tables 1 and 2 are statistically significant with a p-value less than 0.05.

5.3 Baselines

To show the effectiveness of the FairMatch algorithm in improving the exposure fairness of recommendations, we compare its performance with four state-of-the-art algorithms and also two simple baselines:

(1) *FA*IR*: This is the method introduced by Zehlike et al. [48] and was mentioned in Section 2. The method was originally used for improving the representation of the protected group in ranked recommendation lists. However, we use this method for improving the visibility of long-tail items in recommendation lists. We define protected and unprotected groups as long-tail and short-head items, respectively. For separating short-head from long-tail items, we consider those top items that cumulatively take up 20% of the ratings according the Pareto principle [37] as the short-head items and the rest as long-tail items. In addition, we set the other two hyperparameters, proportion of protected candidates in the top n items[8] and significance level,[9] to $\{0.2, 0.6, 0.8\}$ and $\{0.05, 0.1\}$, respectively.

(2) *xQuAD*: This is the method introduced in the work of Abdollahpouri et al. [3] and was mentioned in Section 2. We specifically included the xQuAD method since it attempts to promote less popular items (most likely items with low visibility in recommendation lists) by

[7] For `BPR`, we set all regularizers $\in$ $\{0.0001, 0.001, 0.01\}$, $iterations \in \{30, 50, 100\}$, $learningrate \in \{0.0001, 0.001, 0.005, 0.01\}$, and $factors \in \{50, 100, 150, 200\}$. For `NCF`, we set $epochs \in \{10, 20\}$, $factors \in \{8, 15, 30\}$, and $learningrate \in \{0.001, 0.0001\}$. For `UserKNN`, we set $neighbors \in \{10, 30, 50, 100, 200, 300\}$.

[8] Based on suggestion from the released code, the range should be $[0.02, 0.98]$.

[9] Based on suggestion from the released code, the range should be $[0.01, 0.15]$.

balancing the ratio of popular and less popular items in recommendation lists. This method involves a hyperparameter to control the trade-off between relevance and long-tail promotion, and we experimented with different values for this hyperparameter and set it to $\{0.2, 0.4, 0.6, 0.8, 1\}$. In addition, the separation of short-head and long-tail items is done according to the Pareto principle as described earlier.

(3) *Discrepancy Minimization*: **Discrepancy Minimization (DM)** is the method introduced by Antikacioglu and Ravi [9] and was explained in Section 2. For hyperparameter tuning, we followed the experimental settings suggested by the original work for our experiments. We set the target degree distribution to $\{1, 5, 10\}$ and relative weight of the relevance term to $\{0.01, 0.5, 1\}$.

(4) *ProbPolicy*: This is the method introduced by Mehrotra et al. [32] and was mentioned in Section 2. We included this method as it was designed for improving supplier fairness and visibility in recommendation lists. This method involves a hyperparameter for controlling the trade-off between the relevance of recommended items to users and supplier fairness. We set the value for this hyperparameter to $\{0.2, 0.4, 0.6, 0.8, 1\}$.

We also used two simple methods to show the extreme case in bias mitigation for comparison purposes:

(1) ***Reverse*:** Given a recommendation list of size t for each user generated by the base recommendation algorithm, in this method, instead of picking the n items from the top (the most relevant items), we pick them from the bottom of the list (the least relevant items). In this approach, we expect to see an increase in aggregate diversity as we are giving higher priority to the items with lower relevance to be picked first. However, the accuracy of the recommendations will decrease as we give higher priority to less relevant items.

(2) ***Random*:** Given a recommendation list of size t for each user generated by the base recommendation algorithm, we randomly choose n items from that list and create a final recommendation list for that user. Note that this is different from randomly choosing items from all catalogs to recommend to users. The reason we randomly choose the items from the original recommended list of items (size t) is to compare other post-processing and reranking techniques with a simple random reranking.

Random and *Reverse* are mainly included to demonstrate the extreme version of a reranking algorithm where our sole focus is on improving aggregate diversity and exposure, and we ignore the relevance of the recommended items as can be seen by the low precision for these two algorithms.

One of the hyperparameters involved in our FairMatch algorithm is λ, which controls the balance between the utility of users and suppliers (or items). For our experiments, we try $\lambda \in \{0, 0.25, 0.5, 0.75, 1\}$. A higher value for λ indicates more focus on maintaining the accuracy of the recommendations, whereas a lower value for λ indicates more focus on improving exposure fairness of recommendations. Another hyperparameter in the FairMatch algorithm is β, which determines the fraction of items in original recommendation lists that we want to replace with the identified items in the third step of the FairMatch algorithm. For our experiments, we set $\beta = 0.6$ and $\beta = 1$ for Last.fm and MovieLens datasets, respectively.

5.4 Evaluation Metrics

For evaluation, we use the following metrics to measure different aspects of the effectiveness of each method:

(1) ***Precision* (*P*):** This is the fraction of the recommended items shown to the users that are part of the users' profile in the test set.

(2) ***Item Visibility Shift* (*IVS*):** This is the percentage of increase or decrease in the visibility of item groups in final recommendation lists generated by a reranking algorithm compared to their visibility in recommendation lists generated by a base recommender. Given long recommendation lists of size t, L', generated by a base recommender and the visibility of each item i computed as the fraction of times that it appears in the recommendation lists of different users, we create 10 groups of items based on their visibility in L'. To do so, first we sort the recommended items based on their visibility in L' in descending order, and then we group the recommended items into 10 equal-size bins where the 1st group represents the items with the highest visibility and the 10th group represents the items with the lowest visibility in L'. Item Visibility (IV) of each item i in final recommendation lists can be calculated as

$$IV(i) = \frac{\sum_{j \in L} \mathbb{1}(j = i)}{|L|}, \tag{6}$$

where $\mathbb{1}(.)$ is the indicator function returning zero when its argument is False and 1 otherwise. Item Group Visibility (IGV) for each item group τ can be calculated as

$$IGV(\tau) = \frac{\sum_{i \in \tau} IV(i)}{|\tau|}. \tag{7}$$

Therefore, Item Visibility Shift (IVS) of group τ can be calculated as

$$IVS(\tau) = \frac{IGV(\tau)^{Reranker} - IGV(\tau)^{Base}}{IGV(\tau)^{Base}}, \tag{8}$$

where $IGV(\tau)^{Reranker}$ and $IGV(\tau)^{Base}$ are the visibility of item group τ in recommendation lists of size n generated by the reranking algorithm and the base algorithm, respectively.

(3) ***Supplier Visibility Shift* (*SVS*):** This is the percentage of increase or decrease in the visibility of supplier groups in final recommendation lists generated by a reranking algorithm compared to their visibility in recommendation lists generated by a base recommender. SVS can be calculated similar to IVS, but instead of calculating the percentage change over item groups, we calculate it over supplier groups in SVS. Thus, given long recommendation lists L' generated by a base recommender and the visibility of each supplier s computed as the fraction of times the items belonging to that supplier appear in the recommendation lists of different users, analogous to IVS, we create 10 groups of suppliers based on their visibility in L'. Supplier Visibility (SV) of each supplier s in final recommendation lists L can be calculated as

$$SV(s) = \sum_{s \in g} \sum_{i \in A(s)} IV(i), \tag{9}$$

where $A(s)$ returns the items belonging to supplier s. Supplier Group Visibility (SGV) for each supplier group g can be calculated as

$$SGV(g) = \frac{SV(s)}{|g|}. \tag{10}$$

Therefore, Supplier Visibility Shift (SVS) of group g can be calculated as

$$SVS(g) = \frac{SGV(g)^{Reranker} - SGV(g)^{Base}}{SGV(g)^{Base}}, \tag{11}$$

where $SGV(g)^{Reranker}$ and $SGV(g)^{Base}$ are the visibility of item group g in recommendation lists of size n generated by reranking algorithm and the base algorithm, respectively.

(4) ***Item Aggregate Diversity*** **(**α-IA**):** We propose α-IA as the fraction of items that appear at least α times in the recommendation lists and can be calculated as

$$\alpha\text{-}IA = \frac{\sum_{i \in I} \mathbb{1}\left(\sum_{j \in L} \mathbb{1}(j = i) \geq \alpha\right)}{|I|}, \quad (\alpha \in \mathbb{N}). \tag{12}$$

This metric is a generalization of standard aggregate diversity as it is used in other works [8, 44] where $\alpha = 1$.

(5) ***Long-Tail Coverage*** **(**LT**):** This is the fraction of the long-tail items covered in the recommendation lists. To determine the long-tail items, we separated the top items that cumulatively take up 20% of the ratings in train data as short-head itms and the rest of the items are considered as long-tail items. Given these long-tail items, we calculated LT as the fraction of these items appearing in recommendation lists.

(6) ***Supplier Aggregate Diversity*** **(**α-SA**):** We propose α-SA as the fraction of suppliers that appears at least α times in the recommendation lists and can be calculated as

$$\alpha\text{-}SA = \frac{\sum_{s \in S} \mathbb{1}\left(\sum_{i \in A(s)} \sum_{j \in L} \mathbb{1}(j = i) \geq \alpha\right)}{|S|}, \quad (\alpha \in \mathbb{N}), \tag{13}$$

where $A(s)$ returns all the items belonging to supplier s and S is the set of all suppliers.

(7) ***Item Gini Index*** **(**IG**):** This is the measure of fair distribution of recommended items. It takes into account how uniformly items appear in recommendation lists. Uniform distribution will have Gini index equal to zero, which is the ideal case (a lower Gini index is better). IG is calculated as follows over all the recommended items across all users:

$$IG = \frac{1}{|I| - 1} \sum_{k=1}^{|I|} (2k - |I| - 1) IV(i_k), \tag{14}$$

where $IV(i_k)$ is the visibility of the k-th least recommended item being drawn from L and is calculated using Equation (6).

(8) ***Supplier Gini Index*** **(**SG**):** This is the measure of fair distribution of suppliers in recommendation lists. This metric can be calculated similar to IG, but instead of considering the distribution of recommended items, we consider the distribution of recommended suppliers and it can be calculated as

$$SG = \frac{1}{|S| - 1} \sum_{k=1}^{|S|} (2k - |S| - 1) SV(s_k), \tag{15}$$

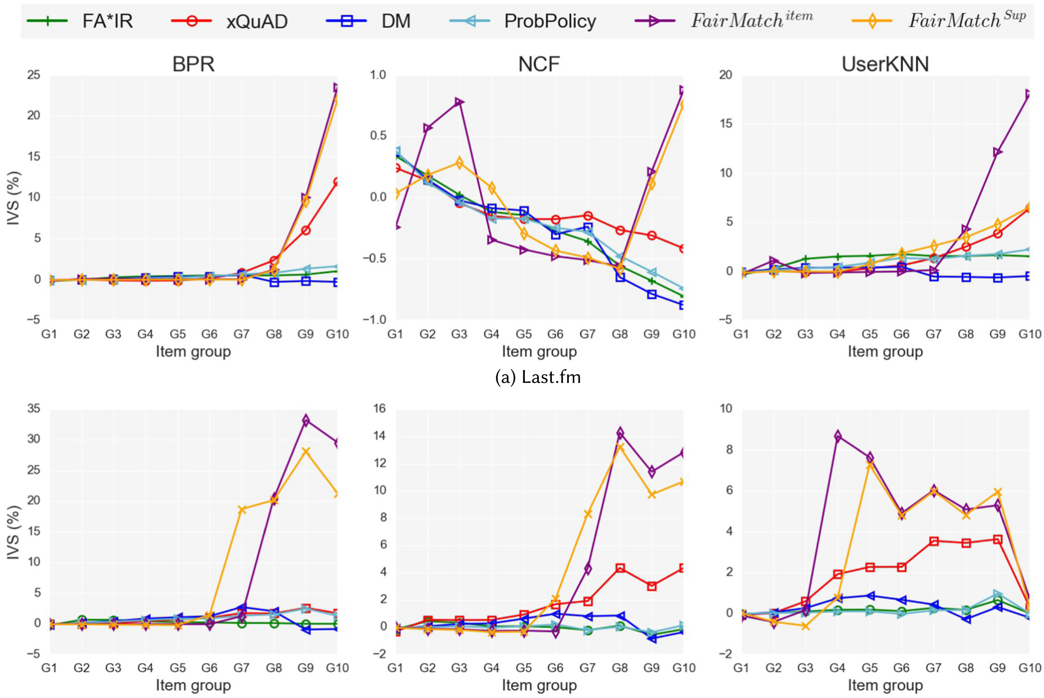
where $SV(s_k)$ is the visibility of the k-th least recommended supplier being drawn from L and is calculated using Equation (9).

(9) ***Item Entropy*** **(**SE**):** Given the distribution of recommended items, entropy measures the uniformity of that distribution. Uniform distribution has the highest entropy or information gain, and thus higher entropy is more desired when the goal is increasing diversity.

$$IE = -\sum_{i \in I} IV(i) \log IV(i) \tag{16}$$

(10) ***Supplier Entropy*** **(**SE**):** This is the measure of uniformity of the distribution of suppliers in the recommendation lists. Similar to Gini where we had both IG and SG, we can also measure the entropy for suppliers as follows:

$$SE = -\sum_{s \in S} SV(s) \log SV(s). \tag{17}$$



(a) Last.fm

(b) MovieLens

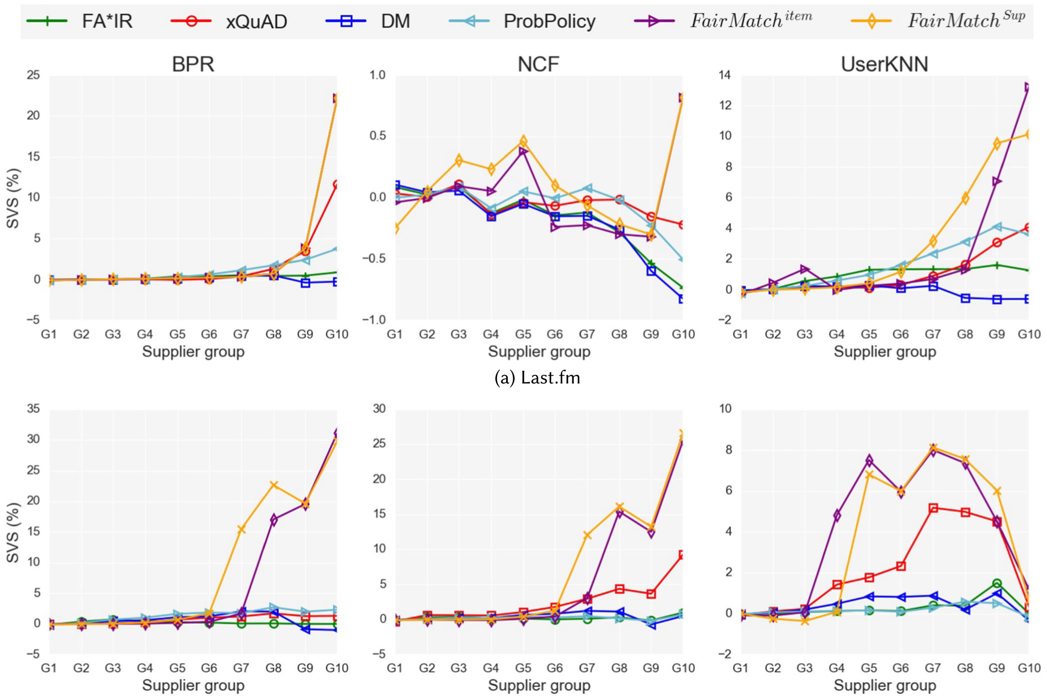
Fig. 9. Percentage increase/decrease (IVS) in visibility of item groups for different reranking algorithms.

6 RESULTS

In this section, we analyze the performance of our FairMatch algorithm in comparison with some of the state-of-the-art reranking algorithms we described in Section 5.3 using three different standard recommendation algorithms as the base for the reranking algorithms on two datasets. Extensive experiments are performed using each reranking algorithm with multiple hyperparameter values. For the purpose of fair comparison, from each of those reranking algorithms (FA*IR, xQuAD, DM, ProbPolicy, and both variations of our FairMatch algorithm), the configuration that yields, more of less, the same precision loss is reported. These results enable us to better compare the performance of each technique on improving exposure fairness and other non-accuracy metrics while maintaining the same level of accuracy. The precision of each reranking algorithm on both datasets is reported in Tables 1 and 2.

6.1 Visibility Analysis

Since our FairMatch algorithm aims at improving the visibility of different items in the recommendations, we start our analysis by comparing different algorithms in terms of the visibility change (IVS) of the recommended items. Figure 9 shows the percentage change in the visibility of the recommended item groups in recommendation lists generated by each reranking algorithm compared to their visibility in the recommendation lists generated by three base recommenders. In these plots, the x-axis is the recommended item groups (created as explained in Section 5.4) and the y-axis is the IVS metric. Item groups are sorted from the highest visibility (i.e., G_1) to the lowest visibility (i.e., G_{10}). It can be seen that both versions of the FairMatch algorithm on both datasets have significantly increased the visibility of item groups with lower visibility while



(a) Last.fm

(b) MovieLens

Fig. 10. Percentage increase/decrease (SVS) in visibility of supplier groups for different reranking algorithms.

slightly taking away from the visibility of items with originally extreme visibility. $FairMatch^{item}$ performs slightly better than $FairMatch^{Sup}$ especially for item groups for very low visibility (G_9 and G_{10}) as was expected since $FairMatch^{item}$ directly optimizes for improving the exposure of the low-visibility items.

Looking at NCF on MovieLens, it seems that different reranking algorithms do not have a predictable behavior in terms of improving visibility of different item groups and, in some cases, even decreasing the visibility of item groups with already low visibility. However, a closer look at the scale of the y-axis reveals that these changes are very small and not significant. The reason is that, on this dataset, NCF has already done a good job in terms of fair item visibility and not much can be done via a reranking method. Among other reranking methods, xQuAD seems to also perform relatively well but still is outperformed by FairMatch. One interesting observation in this figure is that, using UserKNN on MovieLens, we can see that both FairMatch algorithms have significantly improved the visibility of item groups with medium visibility even more than the ones with lower visibility. Although these are items with medium visibility using our grouping strategy, they still get significantly less visibility compared to G_1 and G_2 in the base algorithm as we saw in Figure 1. Therefore, we can still consider these item groups as items with relatively low visibility and FairMatch has increased their visibility.

Figure 10 is similar to Figure 9, but here we show the percentage change in the visibility of the supplier groups in recommendation lists generated by each reranking algorithm compared to their visibility in the recommendation lists generated by three base recommenders. The first thing that can be observed from this figure is that, on both datasets, FairMatch algorithms outperform the other reranking methods especially for groups with lower visibility. NCF on Last.fm has the

Table 1. Comparison of Different Reranking Algorithms on the Last.fm Dataset for Long Recommendation Lists of Size 50 ($t = 50$) and Final Recommendation Lists of Size 10 ($n = 10$)

Algorithms	Baselines	Precision	1-*IA*	5-*IA*	*LT*	1-*SA*	5-*SA*	*IG*	*IE*	*SG*	*SE*
`BPR`	Base	0.097	0.555	0.218	0.53	0.668	0.374	0.693	7.83	0.686	7
	Random	0.062	0.695	0.237	0.678	0.781	0.424	0.568	8.16	0.607	7.23
	Reverse	0.041	0.768	0.243	0.755	0.847	0.455	0.492	8.31	0.564	7.33
	FA*IR	0.096	0.613	**0.242**	0.591	0.715	**0.421**	0.627	8.01	0.642	7.13
	xQuAD	0.094	0.677	0.188	0.659	0.787	0.373	0.646	7.95	0.653	7.1
	DM	0.096	0.644	0.221	0.625	0.736	0.399	0.627	8.01	0.649	7.11
	ProbPolicy	0.092	0.607	0.22	0.586	0.784	0.419	0.659	7.93	0.618	7.19
	$FairMatch^{item}$	0.092	**0.686**	0.223	**0.669**	**0.791**	0.404	**0.602**	**8.08**	0.623	7.19
	$FairMatch^{Sup}$	0.095	0.675	0.21	0.657	**0.791**	0.404	0.623	8.03	**0.617**	**7.22**
`NCF`	Base	0.08	0.638	0.211	0.62	0.754	0.4	0.666	7.95	0.661	7.12
	Random	0.056	0.74	0.221	0.726	0.824	0.441	0.552	8.22	0.592	7.28
	Reverse	0.044	0.791	0.227	0.779	0.857	0.463	0.492	8.34	0.561	7.35
	FA*IR	0.079	0.653	0.21	0.639	0.768	0.41	0.639	8.01	0.639	7.16
	xQuAD	0.075	0.694	0.212	0.683	0.804	0.424	0.61	8.08	0.616	7.22
	DM	0.079	0.723	0.205	0.707	0.808	0.412	0.594	8.11	0.624	7.2
	ProbPolicy	0.072	0.659	0.207	0.643	0.809	0.43	0.647	7.98	0.611	7.22
	$FairMatch^{item}$	0.064	**0.729**	0.224	**0.716**	0.821	0.42	0.589	**8.15**	0.608	7.25
	$FairMatch^{Sup}$	0.071	0.711	**0.229**	0.699	**0.828**	**0.485**	**0.588**	**8.15**	**0.535**	**7.41**
`UserKNN`	Base	0.08	0.461	0.127	0.431	0.588	0.257	0.833	7.07	0.813	6.39
	Random	0.044	0.635	0.164	0.615	0.738	0.341	0.689	7.77	0.702	6.91
	Reverse	0.027	0.712	0.204	0.696	0.797	0.394	0.591	8.09	0.634	7.14
	FA*IR	0.074	**0.629**	**0.172**	**0.609**	0.73	*0.351*	**0.687**	**7.73**	*0.706*	*6.86*
	xQuAD	0.078	0.577	0.117	0.554	0.701	0.269	0.781	7.31	0.771	6.58
	DM	0.077	0.537	0.134	0.512	0.638	0.283	0.782	7.33	0.781	6.55
	ProbPolicy	0.067	0.559	0.14	0.535	0.785	**0.332**	0.765	7.4	0.7	6.84
	$FairMatch^{item}$	0.062	0.626	0.102	0.606	0.751	0.266	0.745	7.51	0.736	6.78
	$FairMatch^{Sup}$	0.073	**0.629**	0.123	**0.609**	**0.895**	0.266	0.73	7.54	**0.659**	**6.97**

The bolded entries show the best values and the underlined entries show the statistically significant change from the second-best baseline with $p < 0.05$ (comparison between FairMatch algorithms and other baselines ignoring Random and Reverse).

same problem as we observed in Figure 9 where the changes in the y-axis are not significant and all algorithms more or less perform equally. $FairMatch^{item}$ and $FairMatch^{Sup}$ are performing equally well for groups with extremely low visibility, although $FairMatch^{Sup}$ tends to also improve the visibility of some other item groups such as G_7, G_8, and G_9 on MovieLens using `BPR` and on Last.fm using `UserKNN`. Overall, $FairMatch^{Sup}$ has done a better job in terms of supplier visibility fairness, and that was also expected since we incorporated supplier visibility directly into our objective function.

In addition to measuring the improvement in visibility of different items, we also conducted an extensive analysis on other existing metrics in the literature to have a better picture of how each of these reranking methods help in reducing the over-concentration of the recommendations around a few highly visible items. Tables 1 and 2 show the results for different reranking algorithms on Last.fm and MovieLens datasets, respectively. We compare these algorithms in terms of item and supplier aggregate diversity and also fair distribution of recommended items and suppliers.

Table 2. Comparison of Different Reranking Algorithms on the MovieLens Dataset for Long Recommendation Lists of Size 50 ($t = 50$) and Final Recommendation Lists of Size 10 ($n = 10$)

Algorithms	Baselines	Precision	1-*IA*	5-*IA*	*LT*	1-*SA*	5-*SA*	*IG*	*IE*	*SG*	*SE*
BPR	Base	0.332	0.392	0.262	0.351	0.418	0.276	0.833	6.01	0.845	5.4
	Random	0.198	0.502	0.359	0.47	0.509	0.365	0.726	6.55	0.773	5.8
	Reverse	0.125	0.547	0.404	0.518	0.545	0.394	0.653	6.81	0.728	6
	FA*IR	0.306	0.402	0.283	0.362	0.4	0.296	0.779	6.33	0.802	5.5
	xQuAD	0.322	0.461	0.311	0.426	0.451	0.324	0.797	6.19	0.822	5.34
	DM	0.314	0.47	0.343	0.435	0.453	0.345	**0.749**	**6.43**	0.791	**5.51**
	ProbPolicy	0.289	0.439	0.297	0.402	0.451	0.343	0.792	6.23	*0.782*	5.49
	$FairMatch^{item}$	0.322	0.544	0.323	0.515	0.536	0.355	0.796	6.17	0.82	5.32
	$FairMatch^{Sup}$	0.311	**0.547**	**0.363**	**0.518**	**0.578**	**0.41**	0.768	6.28	**0.779**	**5.51**
NCF	Base	0.312	0.433	0.286	0.395	0.424	0.297	0.83	6.17	0.848	5.32
	Random	0.198	0.566	0.396	0.539	0.571	0.406	0.728	6.66	0.776	5.89
	Reverse	0.128	0.615	0.448	0.592	0.614	0.446	0.661	6.9	0.735	6.07
	FA*IR	0.296	0.467	0.316	0.432	0.467	0.324	0.786	6.42	0.81	5.58
	xQuAD	0.31	0.535	0.4	0.505	0.556	0.41	0.774	6.26	**0.752**	**5.87**
	DM	0.298	0.53	0.383	0.499	0.509	0.386	**0.752**	**6.54**	0.797	5.6
	ProbPolicy	0.301	0.469	0.315	0.434	0.426	0.344	0.812	6.24	0.819	5.45
	$FairMatch^{item}$	0.301	**0.623**	0.375	**0.6**	0.604	0.397	0.778	6.37	0.81	5.49
	$FairMatch^{Sup}$	0.292	0.622	**0.407**	0.599	**0.62**	**0.446**	0.757	6.45	0.777	5.66
UserKNN	Base	0.190	0.161	0.108	0.102	0.167	0.119	0.889	4.87	0.896	4.13
	Random	0.128	0.219	0.145	0.164	0.231	0.157	0.798	5.51	0.829	4.79
	Reverse	0.093	0.238	0.164	0.185	0.251	0.177	0.728	5.8	0.78	5.06
	FA*IR	0.19	0.166	0.113	0.107	0.175	0.122	0.885	4.9	0.893	4.16
	xQuAD	0.196	0.204	0.136	0.148	0.215	0.148	0.869	4.97	0.88	4.25
	DM	0.19	0.183	0.125	0.125	0.194	0.133	0.873	4.98	0.885	4.22
	ProbPolicy	0.19	0.165	0.11	0.106	0.175	0.122	0.886	4.89	0.891	4.17
	$FairMatch^{item}$	0.19	**0.214**	**0.152**	**0.159**	**0.224**	**0.171**	**0.804**	**5.18**	**0.831**	**4.41**
	$FairMatch^{Sup}$	0.206	0.207	0.131	0.152	0.222	0.158	0.867	4.77	0.871	4.15

The bolded entries show the best values and the underlined entries show the statistically significant change from the second-best baseline with $p < 0.05$ (comparison between FairMatch algorithms and other baselines ignoring Random and Reverse).

6.2 Item Aggregate Diversity

When it comes to increasing the number of unique recommended items (aggregate diversity), we can see that all reranking algorithms have improved this metric over the base algorithms on both datasets. We have only included 1-*IA* (each item should be recommended at least once to be counted) and 5-*IA* (each item should be recommended at least five times to be counted). We experimented with different values of α from 1 to 20, and the results can be seen in Figure 11, which we will describe afterward. Generally speaking, all reranking methods have lost a certain degree of precision to improve aggregate diversity and other metrics related to fair distribution of recommended items and suppliers as can be seen from Tables 1 and 2. The reason is that the base algorithms are mainly optimized for relevance, and therefore it is more likely for the items on top of the recommended list to be relevant to the users. As a result, when we rerank the recommended lists and push some items in the bottom to go up to the top-n, we might swipe some relevant items with items that may not be as relevant.

Regarding 1-IA, $FairMatch^{item}$ seems to perform relatively better than the other rerankers using all three base algorithms (BPR, NCF, and UserKNN) on both datasets, indicating that it recommends a larger number of items across all users. The same pattern can be seen for LT, which measures only the unique recommended items that fall into the long-tail category. This is, however, not the case for 5-IA, where in some cases $FairMatch^{item}$ is outperformed by other rerankers. This shows that the improvement in recommending more unique items using $FairMatch^{item}$ is not achieved by recommending them frequently enough. On MovieLens, however, $FairMatch^{item}$ performs very well on the 5-IA metric. This difference in behavior across the datasets can be explained by the characteristics of the data as we saw in Figure 7. Overall, $FairMatch^{Sup}$ seems to also perform relatively well on item aggregate diversity and in some cases even better than $FairMatch^{item}$, such as on 5-IA using NCF and UserKNN on Last.fm and BPR and NCF on MovieLens.

6.3 Supplier Aggregate Diversity

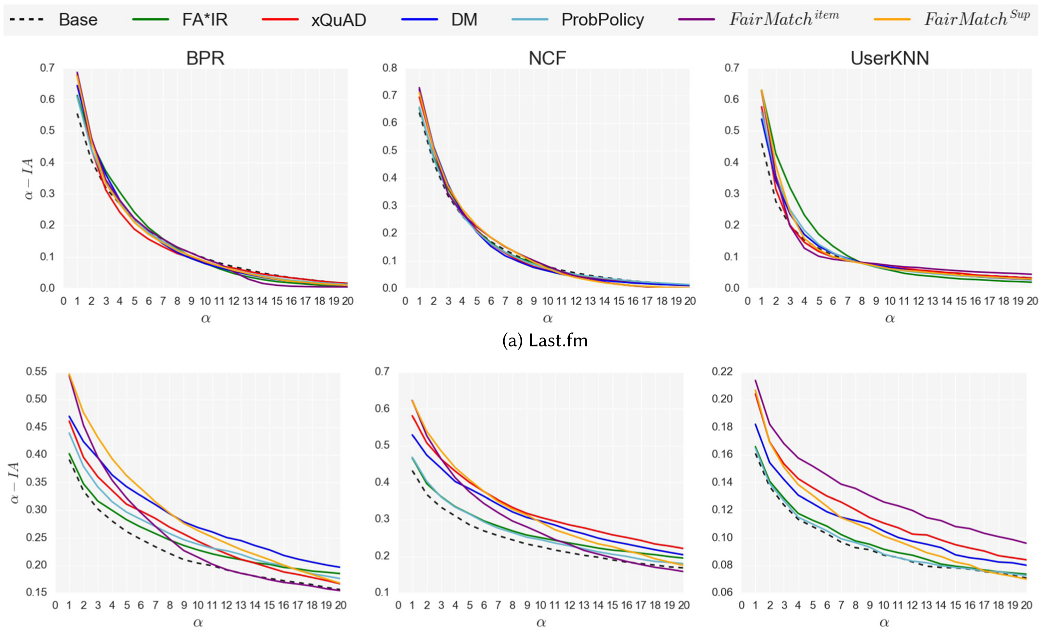
Suppliers of the recommended items are also important to be fairly represented in the recommendations. First and foremost, looking at Tables 1 and 2, we can see that there is an overall positive connection between improving item aggregate diversity and supplier aggregate diversity, indicating that optimizing for either item or supplier visibility can benefit the other side as well. However, when we directly incorporate the supplier visibility into our recommendation process as we did in $FairMatch^{Sup}$, we can see that the supplier aggregate diversity can be significantly improved. For example, we can see that $FairMatch^{Sup}$ has the best 1-SA on both datasets except for when the base algorithm is UserKNN on MovieLens, where it was outperformed by $FairMatch^{item}$. So, overall, we can say that FairMatch (either $FairMatch^{Sup}$ or $FairMatch^{item}$) has the best 1-SA on both datasets using all three base algorithms. Regarding 5-SA, FairMatch algorithms tend to also perform better than other rerankers. Between the two variations of FairMatch, we can see that $FairMatch^{Sup}$ gives a better supplier aggregate diversity in most cases, which is something that we expected. Similar to item aggregate diversity, we only included 1-SA and 5-SA for supplier aggregate diversity in the tables. A more comprehensive analysis of the effect of α on this metric is illustrated in Section 6.6, which we will describe later.

6.4 Fair Distribution of Recommended Items

We also wanted to evaluate different rerankers in terms of fair distribution of recommendations across different items. We used Gini (IG) and Entropy (IE) as ways to measure how equally the recommendations are distributed across different recommended items. Even though we have not optimized directly for equal representation of different items, these two metrics show that our FairMatch algorithm has given a much fairer chance to different items to be recommended compared to the base algorithms and some of the other rerankers by having a low Gini and high Entropy. Between $FairMatch^{Sup}$ and $FairMatch^{item}$, there is no clear winner in terms of Gini and Entropy for items, as in some cases $FairMatch^{Sup}$ has a better Gini while in other cases $FairMatch^{item}$ performs better. Among other rerankers, DM and FA*IR seem to also perform well on these two metrics, indicating that they also give a fair chance to different items to be recommended.

6.5 Fair Distribution of Suppliers in Recommendation Lists

In addition to standard Gini (i.e., IG) and Entropy (i.e., IE), which are generally calculated in an item level, we also measured the same metric but from the supplier perspective, andthis can be seen in Tables 1 and 2 as SG and SE, which measure the extent to which different suppliers are fairly recommended across different users. Overall, $FairMatch^{Sup}$ has the best SG and SE on both datasets in all situations except for NCF and UserKNN on MovieLens. Although using UserKNN on MovieLens, $FairMatch^{item}$ has the second-best SG and SE. This shows that incorporating the



(a) Last.fm

(b) MovieLens

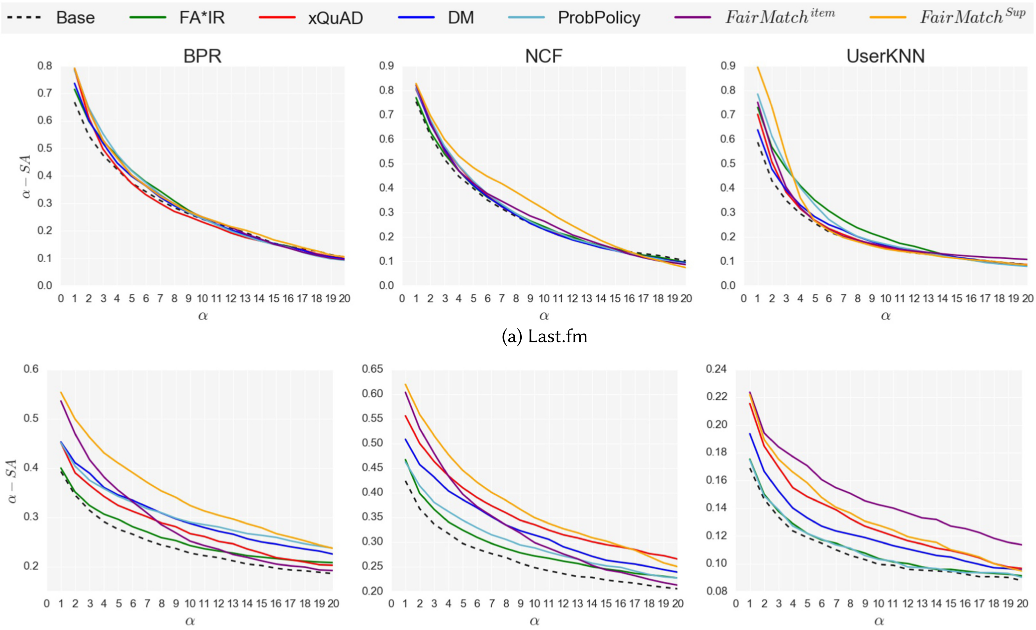
Fig. 11. Comparison of reranking algorithms in terms of item aggregate diversity (α-*IA*) with different α values.

supplier visibility directly into the recommendation process can positively affect the fairness of representation across different suppliers, and it is indeed supporting our initial hypothesis about the importance of incorporating suppliers in the recommendation process. The ProbPolicy algorithm, which also incorporates the supplier fairness in its recommendation generation, has also performed better than other rerankers in terms of *SG* and *SE*.

6.6 The Effect of α in Aggregate Diversity

The standard aggregate diversity metric as it is used in other works [8, 44] counts an item even if it is recommended only once. Therefore, it is possible for an algorithm to perform really well on this metric even though it has not really given enough visibility to different items. For this reason, we introduced α-*IA* and α-*SA*, which are the generalization of standard aggregate diversity where we only count an item or supplier if it is recommended at least α times.

Figures 11 and 12 show the behavior of different reranking algorithms on aggregate diversity for different values of α. The most important takeaway from this figure is that some algorithms perform better than others for smaller values of α, whereas they are outperformed for larger values of α. This means that if we only look at standard aggregate diversity (1-*IA* or 1-*SA*), we might think a certain algorithm is giving more visibility to different items while in reality that is not the case. For example, using BPR as the base on MovieLens, $FairMatch^{Sup}$ has better aggregate diversity for smaller values of α ($\alpha \leq 8$) than DM, whereas for larger values of α, its curve goes under DM, indicating lower aggregate diversity. This shows that if we want to make sure different items are recommended more than eight times, DM would be a better choice, but if we want more items to be recommended even if they are recommended less than eight times, then $FairMatch^{Sup}$ can be better. On supplier aggregate diversity, however, we can see that $FairMatch^{Sup}$ performs better



(a) Last.fm

(b) MovieLens

Fig. 12. Comparison of reranking algorithms in terms of supplier aggregate diversity (α-SA) with different α values.

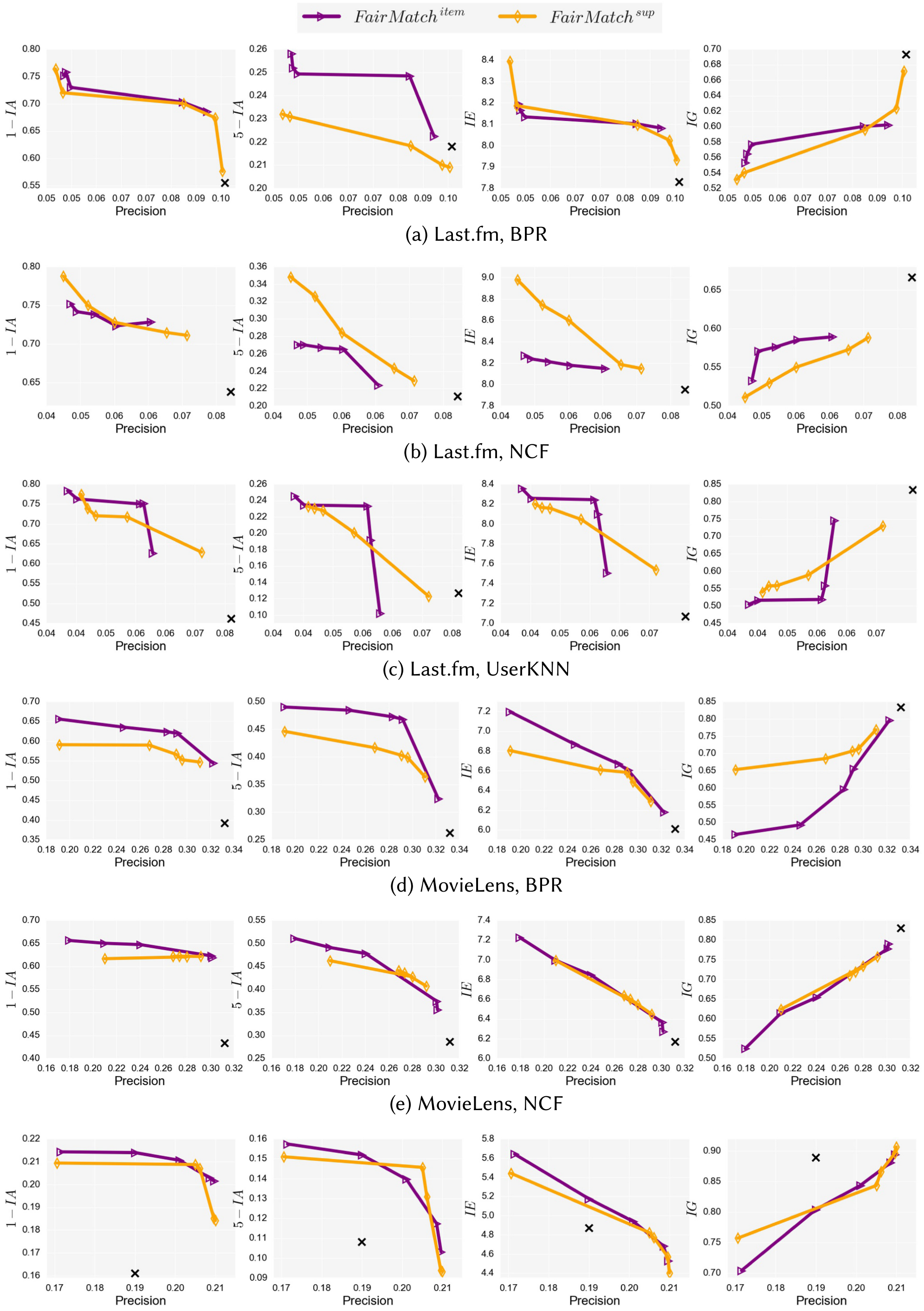
than DM for all values of α, indicating that no matter how frequently we want the recommended items to appear in the recommendations, $FairMatch^{Sup}$ is still superior.

6.7 Trade-Off between Accuracy and Non-Accuracy Metrics for FairMatch

We investigated the trade-off between the precision and non-accuracy metrics under various settings. Figures 13 and 14 show the experimental results for item and supplier exposure, respectively, on Last.fm and MovieLens datasets using all three base recommenders. In these plots, the x-axis shows the precision and the y-axis shows the non-accuracy metrics (i.e., 1-IA, 5-IA, IE, and IG in Figure 13 for measuring item exposure, and 1-SA, 5-SA, SE, and SG in Figure 14 for measuring supplier exposure) of the recommendation results at size 10. Each point on the plot corresponds to a specific λ value, and the black cross shows the performance of original recommendation lists at size 10.

Results in Figures 13 and 14 show that λ plays an important role in controlling the trade-off between the relevance of the recommended items for users (precision) and improving the utility for items and suppliers (non-accuracy metrics). As we decrease the λ value, precision decreases, whereas non-accuracy metrics increase. According to Equations (1) and (2), for a higher λ value, FairMatch will concentrate more on improving the accuracy of the recommendations, whereas for a lower λ value, it will have a higher concentration on improving the utility for items and suppliers.

We only report the results for t = 50, but our analysis on longer initial recommendation lists (e.g., t = 100) showed that by increasing the size of the initial recommendation lists, we will obtain higher improvement on non-accuracy metrics especially on aggregate diversity metrics. However, we will lose accuracy as more items with lower relevance might be added to the final recommendation lists. These parameters allow system designers to better control the trade-off between the precision and non-accuracy metrics.



(a) Last.fm, BPR

(b) Last.fm, NCF

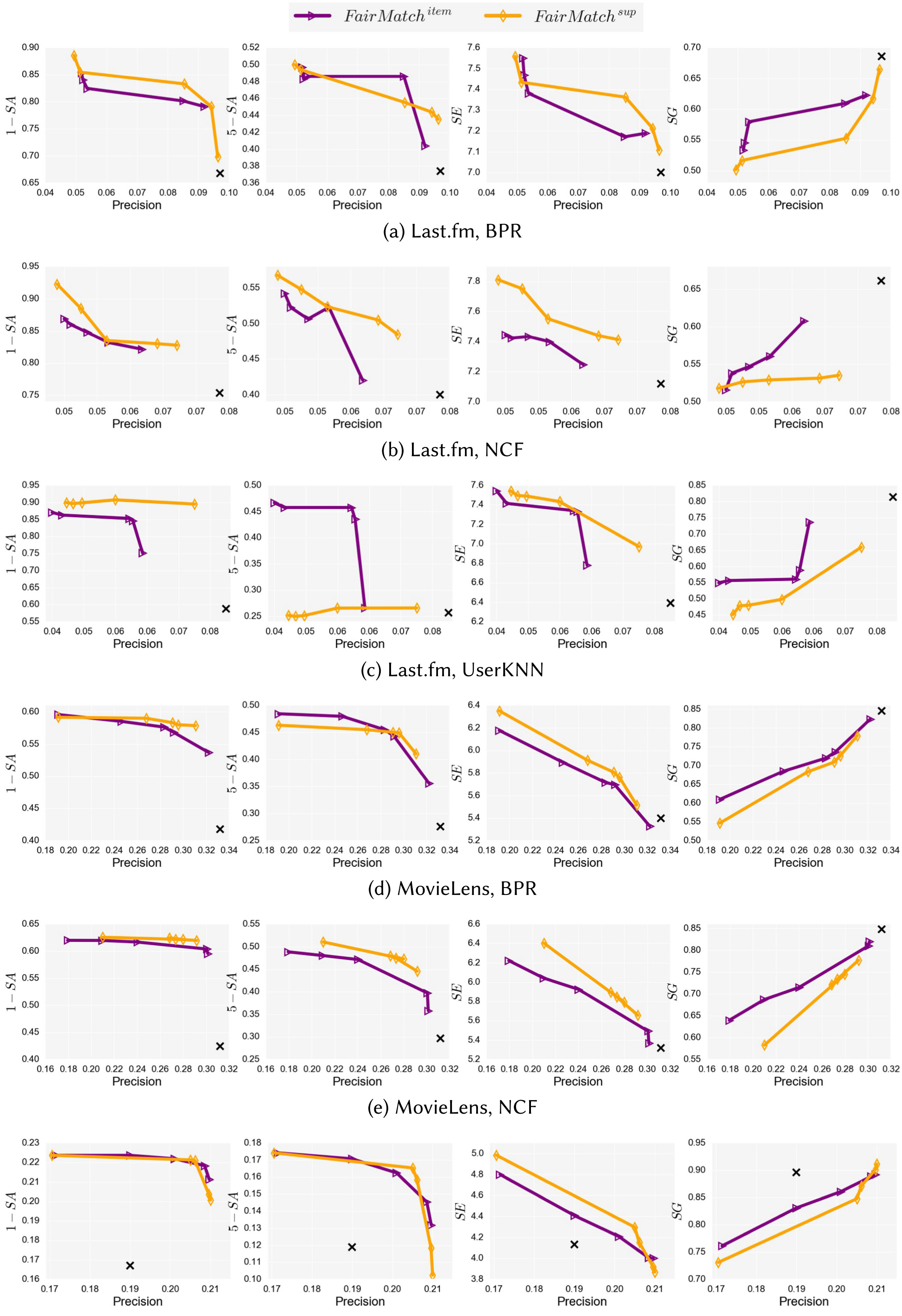
(c) Last.fm, UserKNN

(d) MovieLens, BPR

(e) MovieLens, NCF

(f) MovieLens, UserKNN

Fig. 13. Trade-off between accuracy and non-accuracy metrics for measuring the exposure fairness of items in the FairMatch algorithms on Last.fm and MovieLens datasets using all three base recommenders. The black cross shows the performance of original recommendation lists at size 10.



(a) Last.fm, BPR

(b) Last.fm, NCF

(c) Last.fm, UserKNN

(d) MovieLens, BPR

(e) MovieLens, NCF

(f) MovieLens, UserKNN

Fig. 14. Trade-off between accuracy and non-accuracy metrics for measuring the exposure fairness of suppliers in the FairMatch algorithms on Last.fm and MovieLens datasets using all three base recommenders. The black cross shows the performance of original recommendation lists at size 10.

6.8 Complexity Analysis of the FairMatch Algorithm

Solving the maximum flow problem is the core computation part of the FairMatch algorithm. We used the push-relabel algorithm as one of the efficient algorithms for solving the maximum flow problem. This algorithm has a polynomial time complexity of $O(V^2E)$, where V is the number of nodes and E is the number of edges in bipartite graph. For other parts of the FairMatch algorithm, the time complexity would be in the order of the number of edges, as it mainly iterates over the edges in the bipartite graph.

Since FairMatch is an iterative process, unlike other maximum flow based techniques [8, 9], it requires solving the maximum flow problem on the graph multiple times, and this could be one limitation of our work. However, except for the first iteration that FairMatch executes on the original graph, at the next iterations, the graph will be shrunk as FairMatch removes some parts of the graph at each iteration. Regardless, the upper bound for the complexity of FairMatch will be $O(V^3E)$, assuming in each iteration that we still have the entire graph (which is not the case). Therefore, the complexity of FairMatch is certainly less than $O(V^3E)$, which is still polynomial.

Although FairMatch has a polynomial time complexity, it can be viewed as a limitation for FairMatch, as its complexity is still worse that other baselines introduced in this article. We plan to improve the efficiency of the FairMatch algorithm by proposing a unified model in our future work.

7 CONCLUSION AND FUTURE WORK

In this article, we proposed a graph-based approach, FairMatch, for improving the aggregate diversity and exposure fairness of items and suppliers in recommender systems. FairMatch is a post-processing technique that works on the top of any recommendation algorithm. In other words, it reranks the output from the base recommendation algorithms such that it improves the exposure fairness of final recommendation lists with minimum loss in accuracy of recommendations. Experimental results on two publicly available datasets showed that the FairMatch algorithm outperforms several state-of-the-art methods in improving exposure fairness. In addition, we observed that some of the existing metrics for evaluating the performance of recommendation algorithms in terms of popularity mitigation such as aggregate diversity hides important information about the exposure fairness of items and suppliers, since this metric does not take into account how frequent different items are recommended. Although Gini can be used to address this issue, it also has its own limitations where an algorithm can achieve a good Gini by equally recommending a large number of items or suppliers (even if they are popular), whereas the rest of items or suppliers still get unfair exposure. Our analysis showed that it is crucial to evaluate bias mitigation algorithms using multiple metrics, each of which captures a certain aspect of the algorithm's performance. Our definition of exposure fairness in this article was solely based on the visibility of the items or suppliers in the recommendations without taking into account their original popularity in training data. One possible future work is to take this information into account such that the fairness of exposure for items or suppliers is measured relative to their original popularity as it is done in the work of Abdollahpouri et al. [5]. We also intend to study the effect of our reranking algorithm and other rerankers on the exposure bias of items and suppliers over time where the feedback from the users on recommended items are used in a subsequent training step of the recommendation model known as the feedback loop.

Consistent with many prior work on reranking methods, we observed a drop in precision for different rerankers in our offline evaluation setting. However, how users will perceive the recommendations in an online setting can better assess the effectiveness of this type of rerankers. The reason is that the data is skewed toward popular items and is less likely to observe a hit when recommending less popular items using offline evaluation. Another potential future work is to investigate how users will react to the reranked recommendations by conducting online experiments on real users.

Finally, in this article, we studied the ability of FairMatch for improving exposure fairness items and suppliers in recommender systems. However, FairMatch can be generalized to other definitions of fairness including user fairness. Considering the job recommendation domain where the task is recommending jobs to users, FairMatch can be formulated to fairly distribute "good"jobs (e.g., high-paying jobs) to each group of users based on sensitive attributes (e.g., men and women). We will consider these scenarios in our future work.

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