Private Recommender Systems: How Can Users Build Their Own Fair Recommender Systems without Log Data?

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Abstract

Fairness is a crucial property in recommender systems. Although some online services have adopted fairness aware systems recently, many other services have not adopted them yet. In this work, we propose methods to enable the users to build their own fair recommender systems. Our methods can generate fair recommendations even when the service does not (or cannot) provide fair recommender systems. The key challenge is that a user does not have access to the log data of other users or the latent representations of items. This restriction prohibits us from adopting existing methods designed for service providers. The main idea is that a user has access to unfair recommendations shown by the service provider. Our methods leverage the outputs of an unfair recommender system to construct a new fair recommender system. We empirically validate that our proposed method improves fairness substantially without harming much performance of the original unfair system.

1 Introduction

Fair recommender systems have attracted much attention owing to their importance in society [23]. A typical application is in the job market [9, 8, 10]. The disparate impact theory prohibits a recruiting process that has an adverse impact on a protected group, even if the process appears neutral on its face. Therefore, job recruiters must avoid using unfair talent recommender systems to remove (possibly unintended) biases in their recruiting process.

However, even if users of a service want to adopt fair recommender systems, they cannot utilize them if the service does not provide them. There are several difficulties facing the adoption of fair recommender systems. First, commercial services may be reluctant to implement fair systems because fairness and effectiveness are in a trade-off relation [22, 5], and fairness-aware systems are expensive for implementation and maintenance. Although some social networking services, such as LinkedIn [9, 10], provide fair account recommendations, those of other services, such as Twitter and Facebook, are not necessarily fair with respect to gender or race. Second, the fairness criterion required by a user differs from user to user. The fairness defined by the service may not match the criteria users call for. For example, even if the recommender system is fair with respect to gender, some users may require fairness with respect to race or the combination of gender and race. In general, different fairness criteria are required in different societies. Third, companies may refuse to disclose the algorithms they use. This makes it difficult for users to assess the fairness of the system. Milano et al. [23] pointed out that “The details of RS currently in operation are treated as highly guarded industrial secrets. This makes it difficult for independent researchers to access information about their internal operations, and hence provide any evidence-based assessment.” In summary, it is difficult for users eager to enjoy fair systems to ensure fairness if they use a recommender system provided by a service.

In this paper, we propose a framework where each user builds their own fair recommender system by themselves. Such a system can provide recommendations in a fair manner each user calls for. In this framework, a user uses their own recommender system via a browser add-on instead of the recommender system provided by the service. We call this personal recommender system a private recommender system.

In this work, we focus on item-to-item collaborative filtering, where a set of related items are recommended when a user visits an item page. Each item has a discrete sensitive attribute, such as gender and race. A recommender system must treat all sensitive groups equally. Examples of this setting include:

- **Job recruiting.** Here, a user is a recruiter, an item is a job seeker, and each job seeker has a sensitive attribute, such as gender and race.

- **Breaking the filter bubble [25].** Some recommender systems filter information too aggressively. For example, a news recommender system may recommend only conservative news to conservative users [25]. Some users may want to receive unbiased recommendations with respect to ideology. In this case, the user is a reader, the item is a news article, and each news has an ideology label as the sensitive attribute.
• **Avoiding popular item bias.** Recommender systems tend to recommend popular items too much [31, 22]. Some knowledgeable users need not receive ordinary items, and they may want to receive uncommon items. For example, IMDb recommends Forrest Gump, The Dark Knight, The Godfather, Inception, Pulp Fiction, and Fight Club in the Shawshank Redemption page. However, most cinema fans are already familiar with all of these titles, and these recommendations are not informative to them. In this case, we can set the sensitive attribute to be a popularity label (e.g., high, middle, and low, based on the number of reviews received), such that recommender systems must recommend uncommon (but related) items as well. Although readers may think of this problem as topic diversification [37], we discuss these problems in a unified framework.

We assume that users have access to the sensitive attribute, but they do not necessarily have access to the content of items [17]. Although there exist several methods for building fair recommender systems [30, 26, 20], all of the existing fair recommendation methods are designed for service providers, who can access the entire log data, such as the rating matrix or browsing history of all users. In our setting, however, a user does not have access to the log data of other users or latent representations of items. A clear distinction between this work and previous works is that our setting prohibits accessing such log data. This restriction makes the problem challenging. The key idea is that a user has access to unfair recommendations shown by the service provider. We propose methods to leverage the outputs of an unfair recommender system to construct a fair recommender system. We conduct several experiments and show that our proposed method can build much fairer recommender systems than provider recommender systems while keeping their performance. The contribution of this paper is as follows:

- We propose private recommender systems, where each user builds their own recommender system to ensure the fairness of recommendations. Private recommender systems enable fair recommendations in many situations where conventional recommendation algorithms cannot be deployed. Our proposed framework expands the application scope of fairness-aware recommender systems.

- We propose methods to develop private recommender systems without accessing log data or the contents of items. Although our methods are simple, they exhibit a positive trade-off between fairness and performance, even without accessing log data.

- We confirm that our proposed method works in real-world scenarios via qualitative case studies on IMDb and Twitter.

**Reproducibility:** Our code is available at https://github.com/joisino/private-recsys.

## 2 Notations

For every positive integer \( n \in \mathbb{Z}_+ \), \([n]\) denotes the set \(\{1, 2, \ldots, n\}\). Let \( K \in \mathbb{Z}_+ \) be the length of a recommendation list. Let \( \mathcal{U} = [m] \) denote the set of users and \( \mathcal{I} = [n] \) denote the set of items, where \( m \) and \( n \) are the numbers of users and items, respectively. Without loss of generality, we assume that the users and items are numbered with \(1, \ldots, m\) and \(1, \ldots, n\), respectively.

## 3 Problem Setting

We focus on item-to-item collaborative filtering. In this setting, when user \( u \) accesses the page associated with item \( i \), a recommender system aims to recommend a set of items that are relevant to item \( i \). The recommendation may be personalized for user \( u \) or solely determined by the currently displayed item \( i \). We assume that the recommendation list does not contain any items that user \( u \) has already interacted with. This is natural because already known items are not informative. Formally, a recommendation list is represented by a \( K \)-tuple of items, and a recommender system is represented by a function \( \mathcal{F}: \mathcal{U} \times \mathcal{I} \rightarrow \mathcal{I}^K \) that takes a user and source item and returns a recommendation list when the user visits the source item. \( \mathcal{F}(u, i)_k \) denotes the \( k \)-th item of \( \mathcal{F}(u, i) \).

We assume that each item \( i \) has a sensitive attribute \( a_i \in \mathcal{A} \), and we can observe the sensitive attribute. \( \mathcal{A} \) is a discrete set of sensitive groups. When we cannot directly observe \( a_i \), we estimate it from auxiliary information. A recommender list is fair if the proportion of protected attributes in the list is approximately uniform. For example, \( (\text{man}, \text{man}, \text{man}, \text{man}, \text{woman}, \text{man}) \) is not fair with respect to \( \mathcal{A} = \{\text{man}, \text{woman}\} \) because much more men accounts (items) are recommended than women accounts. We found that LinkedIn employs this kind of fairness in their recommendations. Specifically, at least two men and two women users were recommended out of five recommendation slots in a user’s profile page as far as we observed. However, we observed that Twitter does not employ this kind of fairness. An example of our goal in this paper is to develop a fair recommender system on Twitter, although they do not provide a fair recommender system. In the experiments, we measure fairness quantitatively by least ratio (i.e., the minimum ratio of protected attributes

\[\text{https://www.imdb.com/title/tt0111161/}\]
We assume that user we tackle in this paper is formalized as follows: The provider recommender system is arbitrary and may vate recommender system. Without loss of generality, we have access to the details of the provider recommender system. We call this new recommender system a pri-
stoenable each user to build their own fair recommender system, including the algorithm, latent representations of items, and score function. The only information that we cannot retrieve similar items in different groups. To address this challenge, we propose to utilize the recommendation network to define a similarity measure.

### 4.1 Recommendation Network

Recommendation networks have been utilized to investigate the property of recommender systems, such as the navigation of a recommender system and novelty of recommendations. The node set of a recommendation network is the set of items, i.e., \( V = \mathcal{I} \), and a directed edge \( (i,j) \in \mathcal{I} \times \mathcal{I} \) indicates that item \( j \) is recommended in item \( i \)'s page. They recommend items based on this similarity measure while maintaining fair recommendations. However, the similarities of only \( K \) pairs are defined for each source item in this manner. The recommendation list may solely contain one protected group. In that case, we cannot retrieve similar items in different groups. To address this challenge, we propose to utilize the recommendation network to define a similarity measure.

### 4.2 PrivateRank

In this section, we introduce PrivateRank. First, PrivateRank constructs a recommender network by querying the provider recommender system. We adopt a weighted graph to incorporate
the information of item rankings. Inspired by the discounted cumulative gain, the weight function is inverse-logarithmically discounted. The adjacency matrix \( A \) is defined as:

\[
A_{ij} = \begin{cases} 
\frac{1}{\log(k+1)}(\mathcal{P}_{\text{prov}}(i)_{k} = j) \\
0 
\end{cases} \quad \text{(otherwise)}
\]

PRIVATE\text{RANK} employs the personalized PageRank \cite{15,24}, also called the random walk with restart, which is a classic yet powerful similarity measures between nodes on a graph. The personalized PageRank \( S_{i} \in \mathbb{R}^{n} \) of node \( i \) measures similarities between node \( i \) and other nodes. The personalized PageRank assumes a random surfer who follows a link incident to the current node with probability proportional to its weight or jumps to node \( i \) with probability \( 1 - c \). \( c > 0 \) is a hyperparameter called a damping factor. The damping factor \( c \) controls the spread of random walks. When \( c \) is large, the surfer rarely jumps back to the source node, and it solely captures global structures. Therefore, a small \( c \) is appropriate in capturing local structures around the source node. We empirically demonstrate it in the experiments. The personalized PageRank of node \( j \) with respect to node \( i \) is defined as the probability that the random surfer will arrive at node \( j \). Formally,

\[
S_{i} = c\hat{A}^{\top}S_{i} + (1-c)e^{(i)}
\]

where \( \hat{A} \) is the row-wise normalized adjacency matrix, i.e., \( \hat{A}_{i} = A_{i}/\sum A_{ij} \), and \( e^{(i)} \) is the \( i \)-th standard basis. We compute the personalized PageRank using the cumulative power iteration \cite{34}:

\[
\hat{S}_{i} = (1-c)\sum_{k=0}^{L}c^{k}\hat{A}^{\top}e^{(i)},
\]

where \( L \) is a hyperparameter. \( L \) determines the trade-off between time consumption and accuracy. We find that a small \( L \) is sufficient because recommendation networks are typically small-world. We use \( L = 10 \) in the experiments.

After we obtain the similarity matrix, PRIVATE\text{RANK} ranks items in a fair manner. There are several existing fairness-aware ranking methods, including the optimization-based \cite{30}, learning-based \cite{1}, and post processing-based approaches \cite{9,20,35}. We employ the post processing-based approach similar to \cite{9,20}. We set the minimum number \( \tau \) (\( 0 \leq \tau \leq K/|\mathcal{A}| \)) of items of each group as a hyperparameter. PRIVATE\text{RANK} greedily takes items as long as the constraint can be satisfied. Specifically, let \( r \) be the number of items to be taken, and \( c_{a} \) be the number of items in the list with protected attribute \( a \). Then, if \( \sum_{a \in A} \max(0, \tau - c_{a}) \leq r \) holds, we can satisfy the minimum requirement by completing the list. The pseudo code of PRIVATE\text{RANK} is available in Section B in the appendices.

PRIVATE\text{RANK} holds the following preferable properties. First, it ensures fairness if we increase the minimum requirement \( \tau \).

**Theorem 4.1.** If \( \mathcal{I} \) contains at least \( \tau \) items of each sensitive attribute, the least ratio of recommendation list generated by PRIVATE\text{RANK} is at least \( \tau/K \).

The proof is available in Section C in the appendices.

Second, PRIVATE\text{RANK} does not lose performance when \( \tau = 0 \).

**Theorem 4.2.** If we set \( c < \frac{1}{(K+1)^{2}\log^{2}(K+1)} \), \( L \geq 1 \), and \( \tau = 0 \), the recommendation list generated by PRIVATE\text{RANK} is the same as that of the provider recommender system. Therefore, the recall and nDCG of PRIVATE\text{RANK} are the same as those of the provider recommender system.

The proof is available in Section D in the appendices.

This result is consistent with the intuition that small \( c \) is good for PRIVATE\text{RANK}. These theorems indicate that PRIVATE\text{RANK} properly enhances the functionality of the provider recommender system. Specifically, it can recover the original system when \( \tau = 0 \), and in addition to that, it can control fairness by increasing \( \tau \).

**Time complexity:** We analyze the time complexity of PRIVATE\text{RANK}. Constructing the recommendation network issues \( K \) queries to \( \mathcal{P}_{\text{prov}} \) for each item. Therefore, \( Kn \) queries are issued in total. Computing an estimate \( \hat{S}_{i} \) of the personalized PageRank involves \( L \) vector-matrix multiplications. A vector-matrix multiplication can be done in \( O(Kn) \) time because \( Kn \) elements of \( A \) are non-zero. Therefore, computing \( \hat{S}_{i} \) runs in \( O(KLn) \) time. The postprocessing runs in \( O(K + |\mathcal{A}|) \) time. Hence, constructing the recommendation list takes \( O(n(K + |\mathcal{A}|)) \) time. In total, PRIVATE\text{RANK} runs in \( O(n(KL + |\mathcal{A}|)) \) time if we assume that evaluating \( \mathcal{P}_{\text{prov}} \) runs in a constant time.

**4.3 PrivateWalk** Although PRIVATE\text{RANK} performs well in practice, the main limitation of this method is its scalability. Even if we use a faster approximation method for computing the personalized PageRank, constructing the recommendation network may be a bottleneck of the computation, which requires \( Kn \) evaluations of \( \mathcal{P}_{\text{prov}} \). Many evaluations of \( \mathcal{P}_{\text{prov}} \) may hit the limitation of API, consume too much wall clock time for inserting appropriate intervals, or may be certified as a DOS attack. Therefore, batch methods that construct a full recommendation network are not suitable when
many items are involved. We propose an algorithm to build a private recommender system that computes a recommendation list on demand when a user accesses an item page.

The central idea of PrivateWalk is common with that of PrivateRank: two items are similar if they are close in the recommendation networks of the provider recommender system. PrivateWalk utilizes random walks. Two items \((i, j)\) are considered similar if item \(j\) can be reached from \(i\) in short steps by a random walk. In contrast to PrivateRank, PrivateWalk runs random walks like a web crawler when a user visits a page, rather than building the recommendation networks beforehand. To achieve fairness, PrivateWalk also employs the post-processing approach with the minimum requirement \(\tau\). The pseudo code of PrivateWalk is available in Section E in the appendices.

**Time complexity:** The time complexity of PrivateWalk depends on the average length \(L_{ave}\) of random walks, which is bounded by \(L_{\text{max}}\). PrivateWalk runs the inner loop (Lines 7–14 in the pseudo code) \(KL_{ave}\) time. In each loop, \(P_{\text{prov}.1}\) is evaluated once, CanAdd is evaluated once, and \(O(K)\) basic operations run. The number of loops of the fallback process (Lines 15–19) is a constant in expectation because the probability decays exponentially with respect to the number of iterations. In total, PrivateWalk runs in \(O(K(|A|)L_{ave})\) time if we assume evaluating \(P_{\text{prov}.1}\) runs in constant time. The complexity is independent of the number \(n\) of items in contrast to PrivateRank.

## 5 Experiments

We will answer the following questions via experiments.

- **(RQ1)** How good trade-off between fairness and performance do our proposed methods strike?
- **(RQ2)** How sensitive are our proposed methods with respect to hyperparameters?
- **(RQ3)** Do our methods work in real-world scenarios?

### 5.1 Experimental settings

#### 5.1.1 Datasets

We use four datasets, Adult\(^2\), MovieLens100k \(^1\), LastFM \(^3\), and Amazon Home and Kitchen \(^{13,21}\). In Adult, we recommend a set of people on each person’s page, such that those recommended have the same label as the source person. A recommendation list is considered to be fair if it contains men and women in equal proportion. We use this dataset with talent searching in mind. In MovieLens, we consider two protected groups (i) movies released before 1990 and (ii) movies that received less than 50 interactions. In LastFM and Amazon, items that received less than 50 interactions are the protected groups. We adopt the implicit setting for MovieLens, LastFM, and Amazon datasets. We set the \(ij\)-th element of the interaction matrix to one if user \(i\) has interacted with item \(j\) and zero otherwise. More details about the datasets are available in Section F in the appendices.

#### 5.1.2 Provider Recommender System

To construct private recommender systems, we first define the provider recommender system.

**Adult dataset.** We use a \(K\)-nearest neighbor recommendation for this dataset. It first standardizes features and recommends \(K\)-nearest people with respect to the Euclidean distance for each person.

**MovieLens, LastFM, and Amazon datasets.** We use nearest neighbor recommendation using rating vectors and Bayesian personalized ranking (BPR) \(^{27}\). In BPR, the similarity of items \(i\) and \(j\) is defined as the inner product of the latent vectors of items \(i\) and \(j\). The top-\(K\) similar items with respect to these similarity measures are recommended in both methods. We use the Implicit package\(^4\) to implement both methods.

### 5.1.3 Evaluation Protocol

**Adult dataset.** We evaluate methods using precision, i.e., the ratio of recommended items with the same class label as the source item.

**MovieLens and Amazon datasets.** We adopt leave-one-out evaluation following previous works \(^{14,27}\). We do not adopt negative sampling but full evaluation to avoid biased evaluation \(^{18}\). We evaluate methods using recall@\(K\) and nDCG@\(K\). These metrics are computed for the recommendation list for the second latest item that user \(u\) interacted with. The positive sample is the latest interacted item, which is left out in the dataset.

**LastFM dataset.** This dataset does not contain timestamps. We randomly arrange the interactions and adopt leave-one-out evaluation as in MovieLens and Amazon datasets.

### 5.1.4 Hyperparameters

Throughout the experiments, we set the length \(K\) of recommendation lists to be 10 for both provider and private recommender systems. We set \(c = 0.01\), \(L = 10\) for PrivateRank and \(L_{\text{max}} = 100\) for PrivateWalk. We inspect the trade-off between performance and fairness by varying \(\tau\). We use the default hyperparameters in the Implicit package for

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\(^2\)https://archive.ics.uci.edu/ml/datasets/adult
\(^3\)https://grouplens.org/datasets/hetrec-2011/
\(^4\)https://github.com/benfred/implicit
the BPR. Namely, the number of dimensions is 100, the learning rate is 0.01, the regularization parameter is 0.01, and the number of iterations is 100.

5.2 Fairness and Performance Trade-off (RQ1)

5.2.1 Baselines First, Provider is the provider recommender system. It serves as an upper bound of private recommender systems in terms of accuracy; however, it is unfair. Random shuffles items in random order and recommends items in a fair manner by the same post processing as PRIVATERANK. Oracle is a posthoc fair recommender system that adopts the same backbone algorithm as the provider recommender system and the same post processing as PRIVATERANK. This algorithm corresponds to the posthoc method in [9]. Note that this method is unrealistic and cannot be used in our setting because it does have access to log data. We use Oracle to investigate the performance deviations from idealistic settings. Note that existing methods for C-fairness, such as FATR [36] and Beyond Parity [33], cannot be used as baselines in this setting because we adopt fairness for items in item-to-item recommendations in this work.

5.2.2 Results Figure 1 shows the trade-off between the fairness measures and the performance of the recommender systems. The score reported in parenthesis is the performance of each method when the recommendation is completely fair (i.e., least ratio is 0.5 and entropy is 1.0, not the score at the pointed position).

**Adult** (Figures 1 (a) and (b)): The least ratio of the provider recommendations is 0.152, which indicates that the provider recommendations are not fair with respect to sex. In contrast, our proposed methods can increase fairness by increasing the threshold. In particular, PRIVATERANK strikes an excellent trade-off between fairness measures and precision. It achieves perfect fairness (i.e., least ratio is 0.5 and entropy is 1.0) while it drops precision by only one percent. PRIVATEWALK performs slightly worse than PRIVATERANK but much better than random access. Because the least ratio and entropy have a one-to-one correspondence, we will report only the least ratios in the following because of space limitation.

**MovieLens** (Figures 1 (c) to (h)): Cosine and BPR in the figure represent the type of the provider recommender system, and popularity and period represent the protected attributes. PRIVATERANK strikes an excellent trade-off between accuracy and fairness in all settings. In particular, PRIVATERANK is comparable with the oracle method, which has access to the unavailable information in our setting. It can also be observed that BPR increases the performance of the provider recommender system compared to the cosine similarity, and it also increases the performance of private recommender systems accordingly. This indicates that effective provider recommender systems induce effective private recommender systems. The overall tendencies are common in all set-
we observe similar tendencies in Cosine and BPR for any posthoc processing. (e.g., show the USA and non-USA movies alternatively in the first example if you want.)

Table 1: Case studies on IMDb and Twitter. PrivateWalk can retrieve relevant items in a fair manner, although it does not know the detail of the provider recommender system or have access to log data. Recall that we do not take orders into consideration in the fairness criterion. Once both groups are contained in a recommendation list, it is easy to adjust the order by any posthoc processing. (e.g., show the USA and non-USA movies alternatively in the first example if you want.)

| Source | Toy Story | Toy Story | Toy Story | Toy Story | Toy Story | Toy Story |
|--------|-----------|-----------|-----------|-----------|-----------|-----------|
| 1st    | Toy Story 3 (USA) | Toy Story 3 (USA) | Jim Carrey (man) | Jim Carrey (man) | Jim Carrey (man) | Jim Carrey (man) |
| 2nd    | Toy Story 2 (USA) | Coco (USA) | Hugh Jackman (man) | Sarah Silverman (woman) | Vinton Gray Cerf (man) | Lawrence Lesig (man) |
| 3rd    | Finding Nemo (USA) | The Incredibles (USA) | Samuel L. Jackson (man) | Hugh Jackman (man) | Nigel Shadbolt (man) | Nigel Shadbolt (man) |
| 4th    | Monsters, Inc. (USA) | Spirited Away (non USA) | Dwayne Johnson (man) | Samuel L. Jackson (man) | Andy Dab (man) | Kara Swisher (woman) |
| 5th    | Up (USA) | Castle in the Sky (non USA) | Seth MacFarlane (man) | Emma Watson (woman) | Lawrence Lesig (man) | danah boyd (woman) |
| 6th    | WALL-E (USA) | Howl’s Moving Castle (non USA) | Sarah Silverman (woman) | Alyssa Milano (woman) | Brendan Eich (man) | Adrienne Porter Felt (woman) |

Figure 2: Sensitivity of hyperparameters: Our methods are insensitive to hyperparameters.

ings. These results indicate that our proposed methods can generate effective recommendations in a fair manner regardless of the algorithms used in the provider recommender system and the protected attributes. Because we observe similar tendencies in Cosine and BPR for other datasets, we report only BPR in the following due to space limitation.

LastFM and Amazon (Figures 1 (i) to (l)): Our proposed methods exhibit good trade-off between accuracy and fairness here as well. These results indicate that our proposed methods are effective regardless of the domain of recommendations.

In summary, our proposed methods can achieve perfect fairness, even where the provider recommender systems are not fair, and perform well in various settings.

5.3 Sensitivity of Hyperparameters (RQ2) We investigate the sensitivity of hyperparameters of PrivateRank and PrivateWalk. We fix the minimum requirement τ to be 5 (i.e., perfect fairness) and evaluate performance with various hyperparameters. We evaluate performance by precision for the Adult dataset and by the recall for the other datasets. We normalize these performance measures such that the maximum value is one to illustrate relative drops of performance. Figure 2 (Left) reports the sensitivity of the number L of iterations of the cumulative power iteration, and Figure 2 (Center) reports the sensitivity of the maximum length L_max of random walks. It also shows that this hyperparameter is not sensitive as long as L_max ≥ 100.

5.4 Case Studies in the Wild (RQ3) We run PrivateWalk with real recommender systems in operation in IMDb and Twitter for qualitative case studies. The main goal of this section is to show that our method is feasible even in real-world environments. To the best of our knowledge, there are no existing methods that enable Twitter users to use fair recommender systems. The experiments in this section provide a proof-of-concept that such a challenging task is feasible.

**IMDb:** We found that IMDb recommended only American movies in the Toy Story page\(^5\). Although these recommendations are consistent, they are not informative to cinema fans. We consider whether the movie is from the USA as the protected attribute and run PrivateWalk on IMDb. Table 1 (Left) reports that PrivateWalk also recommends Spirited Away, Castle in the Sky, and Howl’s Moving Castle, which are Japanese animation movies. This result indicates that PrivateWalk recommends in a fair manner with respect to the country attribute while it recommends relevant items.

**Twitter:** As we mentioned in Section 3, we found that Twitter’s user recommendations were not fair with respect to gender, which is in contrast to LinkedIn. We set the protected attribute to be gender and run PrivateWalk on Twitter. We annotate labels and remove non-person accounts manually\(^6\). Table 1 (Middle, Right) reports that PrivateWalk recommends three men users and three woman users in both examples, and all recommended users are celebrity actors for Tom Hanks, and tech-related people for Tim Berners-Lee.

We emphasize that we do not know the recommendation algorithms used in IMDb and Twitter nor have access to log data. Nonetheless, PrivateWalk generates fair recommendations by utilizing blacklist recommendation results. We also point out that PrivateRank is infeasible in this setting because there are too many items in IMDb and Twitter to hit the API limit. In contrast, PrivateWalk runs with few evaluations of the provider recommender systems in an on-demand manner. PrivateRank is beneficial when the number of items is

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\(^5\)https://www.imdb.com/title/tt0114709/

\(^6\)As we mentioned in Section 3, this annotation process can be automated if there is a classifier that takes an account as input and estimates the label.
small (e.g., when we retrieve items only from a specific category) or when we can crawl the website beforehand because it performs better when allowed.

6 Discussion

Limitation. The main limitation of private recommender systems is that it is expensive for each user to develop a system. Although it may still be worthwhile for companies to build their own private recommender systems for a fair recruiting process, most individual users cannot afford to develop their own browser add-ons. We consider two specific scenarios in which individual users benefit from private recommender systems. First, some enthusiastic users of the service can develop browser add-ons and distribute them. For example, a cinema fan may develop a fair private recommender system for IMDb with respect to popularity as a hobby project, such that other IMDb users can enjoy it. Second, general purpose software may help build private recommender systems. In particular, the program we developed in Section 5.4 computes random walks and rankings in common procedures, and we only have to specify in which elements of a web page recommendation lists and sensitive attributes are described. Although users have to write additional scripts for each service in the current version, more elaborated software may further reduce the burden of developing private recommender systems.

We have focused on item-to-item collaborative filtering, which is one of the popular choices in steerable recommender systems [11, 19]. Extending the concept of private recommender systems to other settings, including item-to-user setting, would be fruitful future direction.

Extending recommendation lists. So far, we have assumed that the length of the recommendation lists of the private recommender system is the same as that of the provider recommender system. However, some users may want to know more items than the service provider offers. Our proposed methods can drop this assumption and provide longer lists than the service provider.

7 Related Work

Burke [2] classified fairness of recommender systems into three categories. C-fairness is the fairness of consumers or users of a service, P-fairness is the fairness of producers or items, and CP-fairness considers both sides. In this study, we focused on P-fairness. Note that existing methods for C-fairness such as FATR [36] cannot be applied in this setting. Examples of previous studies on P-fairness are as follows. Geyik et al. [9] proposed a fair ranking of job-seekers in LinkedIn Talent Search. Ekstrand et al. [7] studied book recommendations and found that some recommendation algorithms are biased toward books written by men authors. Beutel et al. [1] were concerned that unfair recommendations in social network services might under-rank posts by some demographic groups, which limits the groups’ visibility. Mehrotra et al. [22] and Patro et al. [26] proposed methods to equalize the visibility of items and realize a fair marketplace. The crucial difference between these studies and our research is that all of these previous methods are for service providers and require log data. In contrast, our methods can be used even without log data and even if a service provider does not offer a fair recommender system. To the best of our knowledge, this is the first work to address this challenging problem.

8 Conclusion

In this paper, we investigated a situation where a service provider does not offer a fair recommender system for the first time. We proposed a novel framework, private recommender systems, where each user builds their own fair recommender system. We proposed PRIVATE-RANK and PRIVATEWALK to build a private recommender system without requiring access to log data. PRIVATE-RANK is effective and exhibits an excellent trade-off between performance and fairness; however, it requires many evaluations of the provider recommender system. Although PRIVATEWALK is less effective, it makes recommendations in an on-demand manner and requires few evaluations of the provider recommender system. The two proposed methods complement each other’s weaknesses. We empirically validated the effectiveness of the proposed methods via offline quantitative evaluations and qualitative experiments in the wild. Our approach realizes fair recommendations in many cases where conventional fair algorithms cannot be deployed, and it promotes the spread of fair systems.

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Generating transparent, steerable recommendations from case study of imdb

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We construct the recommendation network in Line 4 and with item $a_i \in \mathcal{A}$ the transpose of $A$.

$K$ The length of a recommendation list.

$U = [m]$ The set of users.

$I = \{n\}$ The set of users.

$\mathcal{A}$ The set of protected groups.

$a_i \in \mathcal{A}$ The protected attribute of item $i \in \mathcal{I}$.

$\mathcal{P}_{\text{prov}}$ A provider recommender system.

$Q$ A private recommender system.

### Algorithm 1: CanAdd($\mathcal{R}, i$)

1. **Data:** List $\mathcal{R}$ of items, New item $i$.
2. **Result:** Whether we can add item $i$.
3. Initialize $c_a \leftarrow 0 \ (\forall a \in \mathcal{A})$
4. for $j$ in $\mathcal{R} \cup \{i\}$ do
   5. $c_{a_j} \leftarrow c_{a_j} + 1 \quad // \text{Count attributes}$
6. return $\sum_{a \in \mathcal{A}} \max(0, \tau - c_a) \leq K - \text{len}(\mathcal{R})$

### A Notations

Notations are summarized in Table 2.

### B Pseudo Code of PrivateRank

Algorithm 2 describes the pseudo-code of PRIVATERANK. We construct the recommendation network in Line 4 and compute the personalized PageRank in Line 5. In Lines 6–7, we iterate items in the descending order of the personalized PageRank. In Lines 8–9, we add item $i$ to the recommendation list if the user has not interacted with item $i$, and we can preserve the constraint when we insert item $i$.

### C Proof of Theorem 4.1

**Proof.** Let $a_i \in [n]$ be the rank of item $i$ in $\hat{\mathcal{S}}$. Item $i$ appears in the $a_i$-th iteration, and item $\text{ord}_a(a)$ appears in the $a_i$-th iteration of the loop in Lines 7–11 in Algorithm 2. We prove that for each iteration $j \in [n]$ and each sensitive attribute $a \in \mathcal{A}$, $|\{i \in \mathcal{R} \mid a_i = a\} \cup \{i \in \mathcal{I} \mid a_i = a \land a_i \geq j\}| \geq \tau$ holds at the start of the $j$-th iteration. We prove this assertion by mathematical induction. The $j = 1$ case holds because there are at least $\tau$ items of each attribute.

Suppose the proposition holds for $j$. Let $\hat{a} = \text{a}_\text{ord}_a(a)$. The proposition holds for sensitive attribute $a \neq \hat{a}$ because neither $\{i \in \mathcal{R} \mid a_i = a\}$ nor $\{i \in \mathcal{I} \mid a_i = a \land a_i \geq j\}$ changes in the $j$-th iteration. If $|\{i \in \mathcal{R} \mid a_i = \hat{a}\}| \geq \tau$ holds in the $j$-th iteration, the proposition holds for $\hat{a}$. Otherwise, item $\text{ord}_a(a)$ is adopted in the $j$-th iteration because $\sum_{a \in \mathcal{A}} \max(0, \tau - c_a)$ decreases by one, and CanAdd returns True. Therefore, $|\{i \in \mathcal{R} \mid a_i = a\}|$ increases by one, and $|\{i \in \mathcal{I} \mid a_i = a \land a_i \geq j\}|$ decreases by one at the $j$-th iteration. From the inductive hypothesis, the proposition holds for $j + 1$. Therefore, $|\{i \in \mathcal{R} \mid a_i = a\}| \geq \tau$ holds true at the end of the procedure for each attribute $a \in \mathcal{A}$.

### D Proof of Theorem 4.2

**Proof.** Let $D = \sum_{i=1}^{K} \frac{1}{\log(k+1)}$. From the definition,

$$
\hat{S}_i = (1 - c)e(i) + (1 - c)c^T \left( \sum_{k=0}^{L-2} (cA^T)^k e(i) \right).
$$

Therefore, for the $k$-th item $j$ of $\mathcal{P}_{\text{prov},1}(i)$,

$$
\hat{S}_{ij} \geq (1 - c)c^T e(i)j = (1 - c)c^T \frac{1}{D \log(k+1)}.
$$

Suppose $c < \frac{1}{(K+1)^2 \log^2(K+1)}$ holds, then,

$$
\|cA^T \sum_{k=0}^{L-2} (cA^T)^k e(i)\|_\infty \\
\leq c\|A^T\|_1\|\sum_{k=0}^{\infty} (cA^T)^k\|_1\|e(i)\|_1 \\
\leq c\|A^T\|_1\frac{1}{1 - \|cA^T\|_1}\|e(i)\|_1 \\
\leq \frac{c}{1 - c} = \frac{1}{(K+1)^2 \log^2(K+1) - 1} \\
< \frac{1}{D(K+1) \log^2(K+1)} < \frac{1}{D},
$$

where $\|a\|_1$ is the induced norm. Therefore, for $l \notin \mathcal{P}_{\text{prov},1}(i) \cup \{i\}$,

$$
\hat{S}_{il} = (1 - c)c^T \sum_{k=0}^{L-2} (cA^T)^k e(i) < (1 - c)c^T \frac{1}{D \log(K+1)},
$$

and the $k$-th item $j$ of $\mathcal{P}_{\text{prov},1}(i)$,

$$
\hat{S}_{ij} < (1 - c)c^T \frac{1}{D \log(k)}.
$$

Therefore, the top-$K$ ranking does not change.

### E Pseudo Code of PrivateWalk

Algorithm 3 presents the pseudo-code of PRIVATEWALK. Cat$(\theta)$ denotes a categorical distribution of parameter.
We add the fallback process in Lines 15–19 to make the algorithm well-defined. If we cannot find an appropriate item in Lines 15–19 with high probability in practice. Note that we can determine an item in Lines 7–14 with high probability in practice. We add the fallback process in Lines 15–19 to make the algorithm well-defined.

F Datasets

- Adult [6]. In this dataset, each record represents a person and contains demographic data such as age, sex, race, educational background, and income. This dataset has been mainly adopted in supervised learning [16, 32], where the covariates are demographic attributes, and the label represents whether income exceeds $50,000 per year. We use this dataset for individual recommendations. We regard an individual record as a talent and consider it to be fair if it contains men and women in equal proportion. We adopt the same preprocessing as [32]. After preprocessing, this dataset contains 30190 items and 112 features. We set sex as the protected attribute. We use this dataset with talent searching in mind.

- MovieLens100k [12]. In this dataset, an item represents a movie. It contains 943 users, 1682 items, and 100000 interactions in total. Each user has at least 20 interactions. We consider two protected attributes. The first is based on periods of movies. Some recommender systems may recommend only new movies, but some users may want to know old movies as well. We divide movies into two groups, such that the protected group contains movies that were released before 1990. The second protected attribute is based on popularity. Movies that received less than 50 interactions are considered to be in the protected group.

- LastFM 7. In this dataset, an item represents a piece of music. To discard noisy items and users, we extract 10-cores of the dataset, such that each user and item have at least 10 interactions. Specifically, we iteratively discard items and users with less than 10 interactions until all items and users have at least 10 interactions. It contains 1797 users, 1507 items, and 62376 interactions in total after preprocessing. We consider popularity as a protected attribute.

7https://grouplens.org/datasets/hetrec-2011/
The protected group contains music that received less than 50 interactions.

- Amazon Home and Kitchen [13, 21]. In this dataset, an item represents a home and kitchen product on amazon.com. We extract 10-cores of the dataset using the same preprocessing as in the LastFM dataset. It contains 1395 users, 1171 items, and 25445 interactions in total after preprocessing. We consider popularity as a protected attribute. The protected group contains products that received less than 50 interactions.