Self-Determined Reciprocal Recommender System with Strong Privacy Guarantees

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ABSTRACT

Recommender systems are widely used. Usually, recommender systems are based on a centralized client-server architecture. However, this approach implies drawbacks regarding the privacy of users. In this paper, we propose a distributed reciprocal recommender system with strong, self-determined privacy guarantees, i.e., local differential privacy. More precisely, users randomize their profiles locally and exchange them via a peer-to-peer network. Recommendations are then computed and ranked locally by estimating similarities between profiles. We evaluate recommendation accuracy of a job recommender system and demonstrate that our method provides acceptable utility under strong privacy requirements.

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1 INTRODUCTION

Recommender systems support users in their search for relevant information, products, and services by presenting items to a user that match her preferences or needs. In a reciprocal recommender system, users are recommended to each other. These recommendations are different from one-sided product recommendations, where products are recommended to the user but not vice versa. A typical example for reciprocal recommender systems are dating platforms, where people search for a matching partner [28]. Other areas that use two-sided recommender systems are mentoring systems and job recommendations—the use case of our work.

Most existing reciprocal recommender systems provide a platform that connects users to each other. The systems are based on a centralized client-server architecture. In order to receive recommendations, users disclose a significant amount of personal data to create a user profile, which is collected and stored on a server. This approach poses a serious threat to users’ privacy and data control.

In this paper, we propose a content-based distributed recommendation approach. We develop a distributed recommender system in which users exchange their profiles directly to calculate similarities and to receive recommendations. By following this approach, users determine whom to share the data with and therefore gain control over their data. To this end, we use Bloom filters [5] to encode user profiles and apply the randomized response technique (RRT) to provide strong privacy guarantees, i.e., differential privacy [8]. In order to exchange user profiles, we avoid a central architecture. At the same time, we believe that a synchronous peer-to-peer (P2P) network would not be practically viable. Instead, we propose to exchange data via a P2P data network, specifically the InterPlanetary File System (IPFS) [3], which offers asynchronous data access.

We apply and discuss our approach in the context of a P2P job marketplace, which we use as running example. Not only since the EU’s General Data Protection Regulation (GDPR), processing personal data is regulated. In particular, personal data are considered sensitive and require special protection. Hence, we believe that a job marketplace is an ideal use case as it has two sides (recruiters and candidates) and emphasizes the data protection needs.

In our evaluation, we expose the impact of the privacy guarantees on utility. In particular, we show that comparable utility can be achieved using a Bloom filter to encode profiles, instead of a binary vector. Even for strong privacy guarantees ($\epsilon < 10$), parameters can be found which recommend more than 75% of the top 20 candidates accurately with high precision for the top ranked candidates.

The main contribution of our work is to provide a distributed reciprocal recommender system that is self-determined and offers strong privacy guarantees. The remainder of this paper is organized as follows: We describe our running example, the P2P job marketplace in Section 2. In Section 3, we introduce our privacy-preserving recommendation system and provide information about the privacy guarantees. Subsequently, we describe data distribution in Section 4. In Section 5, we evaluate our system regarding the privacy-utility trade off. We review related work in Section 6 and conclude the paper in Section 7.

2 USE CASE: JOB MARKETPLACE

Recommender systems are usually implemented as centralized platforms. This however makes the platform less self-determined, prone to data breaches, and implies privacy risks. In order to emphasize
this situation, we use a job marketplace as running example. According to the GDPR, processing Human Resource (HR) data is allowed under restricted circumstances and increased means of data protection only. In particular, it is difficult for consent to be freely given by job candidates, meaning that it is unlikely to provide a valid basis for processing HR data. Therefore, the marketplace is a relevant example for a distributed system with self-determined data control.

Example: Two-sided Job Marketplace. In recent years, recruiting and selection processes are part of the success of the organization’s future growth and retention of employees. The marketplace is divided into two parts: job recommendation and candidate recommendation [15]. Matching jobs with candidates is based on similarities of the corresponding profiles. These profiles may include features that consist of keywords extracted from job requirements and candidate skills/preferences. That is, job candidates receive suitable job recommendations and recruiters receive candidate recommendations for a job. More specifically, top ranked jobs or the top ranked candidates that best fit the candidate profile or job profile, respectively, are returned. The marketplace can therefore be classified as a reciprocal recommender system.

On the marketplace, recruiters provide a job description including a job profile with requirements and necessary meta-data for the job application. Candidates, interested in using the marketplace, can provide their profile including skill set or interests, or only receive job profiles to calculate possible recommendations. Since job profiles contain no personal information, we assume that they can be made publicly available. Moreover, we assume that marketplace users (candidates and recruiters) are globally distributed. The system is most suitable for global inter- or intra-company recruitment.

Our approach concentrates on the recommendation process. The recommendation procedure takes place outside of the marketplace, thus it is out of scope of this work.

3 RECOMMENDATION APPROACH

In this section, we describe the profile representation and the similarity score for our privacy-preserving content-based recommendation approach. Content-based recommendations use features of items and compute similarities between items to recommend similar items that users have preferred in the past. That means for the proposed marketplace, we assume that candidates prefer jobs that are similar to their previous jobs.

3.1 Profile Representation

The job profiles as well as the candidate profiles are based on keywords extracted from job requirements and candidate skills, respectively. This set of keywords can be represented as a vector.

While in principle the overall set of keywords is finite and well defined, the number of possible keywords can be very large and new keywords may not appear in new jobs. Therefore, we propose to use a probabilistic data structure to represent profiles, keep the memory footprint small, and to be able to handle unknown keywords.

Hence, we represent the set of keywords in a Bloom filter [5]. Bloom filters have been introduced to approximate membership queries but can also serve as item representation for recommender systems [20]. The data structure of a Bloom filter consists of a bit array of a fixed length \( m \) using \( k \) different hash functions [5]. At the beginning, the Bloom filter is empty, i.e., all bits in the array are set to 0. The hash function \( h_i(x) \) with \( i \in \{1, \ldots, k\} \) takes an input \( x \) and determines a position in the bit array that is accordingly set to 1. Membership of a value \( x \) can be tested by repeating the process and checking all respective positions \( h_i(x) \) in the array. If there is at least one bit set to 0, the value \( x \) is not member of the Bloom filter. If all corresponding bits are set to 1, the value \( x \) may be a member of the Bloom filter, but we cannot be certain. Due to bit collisions, influenced by the parameters \( m \) and \( k \), false positives can occur.

For our use case, each job/candidate profile consists of a Bloom filter of the same length and with the same number of hash functions. In Figure 1, we sketch the procedure of adding the keywords to the Bloom filter. Assume for example the job profile "data analyst" has the keywords "statistics" and "python". These keywords are hashed and the corresponding bits are set to 1.

\[
\begin{align*}
B_j & = \text{job "data analyst"} : \{1, 0, 1, 0, 1\} \\
& \quad \text{"statistics"} \\
& \quad \text{"python"}
\end{align*}
\]

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Figure 1: Process of adding keywords to a Bloom filter with \( k = 2 \) and \( m = 5 \).

3.2 Job Recommendation

In order to obtain recommendations, candidates can derive personalized recommendations locally without disclosing their profile. To this end, we use the cosine similarity as metric as it is directly applicable to vectors and widely used in content-based recommender systems [22]. That is, candidates download the Bloom filter of a job offering \( B_j \) and compare it to their own Bloom filter \( B_c \). They calculate the cosine similarity of the two Bloom filters, given by

\[
\cos \theta = \frac{B_j \cdot B_c}{\|B_j\| \|B_c\|}, \quad (1)
\]

where the numerator is the scalar product.

Since our proposed recommender system is self-determined, candidates can identify the top \( N \) jobs with the highest similarity. Additionally, candidates can also set a threshold value, i.e., jobs with a similarity higher than a customizable value are recommended.

3.3 Candidate Recommendation

A recruiter needs candidate profiles to obtain the top \( N \) candidates for her job offering. We assume that the recruiter has received candidate profiles in the representation of a Bloom filter as described in the previous section.

Due to the false positive rate of a Bloom filter, there is a certain uncertainty that provides some privacy. For example in Figure 1, a hash value of "statistics" and "python" are both mapped to the
same bit (5th bit). While this provides some privacy, it is unable to guarantee strong privacy [4]. For example, an adversary could still determine that a profile does not have certain keywords by inspecting the bits set to 0.

Our goal is therefore to offer strong privacy guarantees for profiles, i.e., differential privacy which enables plausible deniability [8]. Differential privacy is a strong privacy definition, providing privacy guarantees to the input of a computation regardless of the amount of background knowledge of an adversary. Local differential privacy (LDP) satisfies differential privacy in the local setting. In other words, a data collector is not trusted and therefore candidates perturb their profile locally.

A function $f$ provides $\epsilon$-differential privacy [8] if for all neighboring pairs of profiles $B$ and $B'$ and all $S \subseteq \text{Range}(f)$ satisfy
\[
P[f(B) \in S] \leq e^{\epsilon} P[f(B') \in S].
\] (2)
In other words, the result of $f$ should be similar independent of the input, i.e., it is irrelevant whether a candidate reports $B$ or $B'$.

LDP is guaranteed by flipping the bits of the Bloom filter based on the RRT, a method used for surveys [27]. With a probability $p$, the bit of the Bloom filter is flipped, i.e., a 1 changes to 0 and vice versa a 0 to 1. Otherwise, the bit is not changed and remains the same. In other words, each bit in the Bloom filter (0 and 1) yields plausible deniability as it remains unclear whether a set bit is a result of randomization or truly corresponds to a certain keyword. Differential privacy is guaranteed with $p = \frac{1}{1 + e^{\epsilon}}$.

A candidate distributes the differentially-private Bloom filter $B_c'$ to recruiters. The recruiter can then calculate the scalar product between the perturbed candidate’s profile $B_c'$ and the job profile $B_j$ to determine the similarity between the candidate and job profiles. Due to the randomization, however, he obtains a perturbed scalar product $\hat{S}P$. To obtain an unbiased cosine similarity, the scalar product is corrected with the number of 1 in the candidates perturbed Bloom filter $\|B_c'\|_1$ according to [1] by
\[
\hat{S}P = \frac{\hat{S}P - p \|B_c'\|_1}{1 - 2p}.
\] (3)
The cosine similarity is then calculated with the corrected $\hat{S}P$ and Equation (1). For more details, we refer the reader to [1]. Note that correcting the scalar product only removes noise from the similarity, not from the candidate Bloom filters, effectively preserving privacy.

4 CONTENT DISTRIBUTION & STORAGE

The recommendation is calculated locally. Therefore, candidates and recruiters need to exchange candidate and job profiles, respectively. Recruiters and candidates effectively build a P2P network. In a naive approach, the P2P network needs to be synchronous to enable direct exchange between recruiters and candidates. While we might be able to assume that recruiters are available at all times, candidates can go offline unexpectedly.

We therefore propose to use the InterPlanetary File System (IPFS) as distributed storage layer, which we illustrate in Figure 2. IPFS is a data network [6], offering distributed data storage and sharing. IPFS allows to distribute candidate and job profiles asynchronously without introducing a central server. IPFS therefore combines the best of both worlds and users gain more control over their data. Data is stored only on a user’s device and only replicated on demand.

![Figure 2: Privacy-preserving recommender system where profiles are exchanged via IPFS.](https://file.app/)

IPFS uses the libp2p library for its network layer and the Bitswap protocol [7] for exchanging data. Files are split into blocks. The blocks are used to build a Merkle Directed Acyclic Graph (DAG). Blocks are content-addressed and exchanged based on their Content Identifier (CID). The CID is derived from the content. Exchanging a file requires the root CID of the Merkle DAG. Blocks contain information of their children and acquiring the DAG results in the file. Blocks are found by requesting neighbors or querying a Kademlia-based Distributed Hash Table.

For our use case, we face three main challenges: ensuring profile availability, job and candidate profile discovery, and access control.

4.1 Profile Availability

In order to ensure the data is available even after a node leaves the network, data has to be replicated by multiple peers of the network. In IPFS, data is replicated passively, by volunteers or cache-based. Initially, data is made available by a single node only (the data source), and will be available as long as the node remains online. In addition, cache-based replication improves availability of popular content. In order to ensure asynchronous availability, however, data needs to be actively replicated. For active replication, there are two possibilities: Filecoin [21] and IPFS Cluster.

Filecoin is a blockchain-based incentive layer, where storage and retrieval of data is compensated via the filecoin token (FIL). In a job marketplace, this generally might be a feasible option: recruiters pay a fee to make the job profiles available, increasing the range of possible candidates. Candidates pay the fee to make their profiles available to increase their consideration for job offerings. At the time of writing storing data in Filecoin costs around 4.8pFIL/GiB for one epoch (30 s)\(^1\) and the minimum duration for storage deals is 180 d. The costs are therefore low with roughly 2.5 pFIL to store 1 GiB (1 FIL ≈ 72$)\(^2\) and negligible for our use case. Nevertheless, we believe that using Filecoin is more suitable for an inter-company marketplace than an intra-company marketplace. In an intra-company marketplace, it might be questionable, who would be willing to pay for storage. In general though, the main disadvantage is that using Filecoin introduces a blockchain and can

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1. [https://file.app/](https://file.app/) (2021-06-03)
2. [https://coinmarketcap.com/en/currencies/filecoin/](https://coinmarketcap.com/en/currencies/filecoin/) (2021-06-03)
therefore introduce additional privacy problems. A blockchain is an immutable public ledger, and therefore reveals information about the pseudonymous participants.

Instead, IPFS Cluster provides the possibility for pinset orchestration. The cluster ensures the availability of files by managing a certain degree of replication (the pinset) between the cluster peers. It actively replicates data, even when nodes leave the cluster. The cluster peers build an overlay network, separate from the IPFS overlay network, and the replication is independent from the IPFS network. Hence, recruiters build a cluster to increase the availability, ensuring candidates can acquire available job profiles. Additionally, the cluster can replicate candidate profiles, if candidates give their consent. Since recruiters have a strong interest to make job profiles constantly available, IPFS Cluster is a viable solution to offer asynchronous, yet distributed and self-determined, data sharing.

4.2 Profile Discovery

In order to query candidate and job profiles, marketplace users need to know the respective CIDs of profiles. Specifically, data is addressed by the root CIDs of the Merkle DAG. Since CIDs are based on the content, changing data changes the CID and CIDs are in general not human-readable. As a result, we need a mechanism to inform marketplace users of existing job and candidate profiles.

To this end, we utilize the Publish/Subscribe (pubsub) architecture from libp2p to announce CIDs. In the network, peers subscribe to a topic, i.e., job or candidate profiles, and are informed of published content. That is, recruiters publish their job profile in IPFS and distribute the respective root CID in the network, where subscribed candidates receive new CIDs and use it to retrieve the profile. Similarly, candidates can publish their profile and recruiters receive the candidate profiles. The information is disseminated in the network via gossiping.

While pubsub ensures that active users receive new messages, new users also want to receive information about relevant profiles. Therefore, a bootstrapping mechanism for CIDs is necessary. To this end, we maintain a list of CIDs. After creating a new profile, the list is updated and new data can be identified. Due to content-addressing of CIDs, the list’s CID changes with every update. In order to address this issue, we suggest to use IPFS’s name service, i.e., Interplanetary Name System (IPNS) that maps the hash of a public key to a CID. That is, changing content changes the mapping, effectively informing about the availability of new job profiles. The maintenance of the file itself will be managed by the IPFS Cluster. If candidates do not want to share their data with potentially everyone on the marketplace, they can share their data deliberately using an out-of-band channel, e.g., sending an e-mail with the CID.

4.3 Access Control

A downside of IPFS is the lack of built-in data access control. Once shared, data subjects lack control over replication and access of data. Moreover, there is no dedicated way to delete data. In general, everyone can request all blocks and curious users can observe requested/announced CIDs. Since we consider job offerings public anyway, the lack of access control is not a problem. However, candidate profiles contain personal data such as name and therefore need additional protection. We suggest to use encryption of candidate profiles to maintain confidentiality. The decryption key is then used as a way to gain access by sharing it only deliberately via other channels with selected individuals. Some research proposes a blockchain for managing access and sharing decryption keys [26].

5 EVALUATION

We perform our evaluation on a real dataset provided by the online employment website Careerbuilder. The dataset contains, inter alia, information about job postings, candidates, and their application history. For our training set we randomly select 10,000 job postings from the job dataset. The candidate profiles are generated from the application history. To this end, we selected all users with at least five applied jobs that are in the job posting dataset as well. Our test dataset for recommending candidates consist of new jobs of the training set that none of the candidates have in their application history. In total, we have 10,000 jobs, 128 candidate profiles, and 7,175 open jobs profiles.

We assume that the requirements for a job offering are vectorized. Therefore, we extract keywords from job titles, descriptions, and requirements by using TF-IDF (term frequency-inverse document frequency), a commonly used scheme. Keywords that occur frequently in one job (term frequency), but rarely in other job profiles (inverse document frequency) have a higher score and are more likely to be relevant to describe a job. For each job, we used all keywords. In total, each job is on average described by 176 keywords (min 2 keywords; max 588 keywords).

In the experiment, we evaluate the candidate recommendation. More specifically, for each job offering, we compute the cosine similarity for each applied job in the candidates profile. In order to generate candidate recommendation, we rank the candidates according to their mean similarity of their applied jobs.

In our evaluation, we aim at comparing the utility of computed recommendations of the binary vector model with a Bloom filter model (bf) and a Bloom filter model with differential privacy guarantees (bf-DP). The binary vector uses a binary representation of the keywords of each job and represents our ground truth. In the other two models, keywords are added to Bloom filters. Additionally, in bf-DP, the Bloom filter is perturbed according to an \( \epsilon \).

We evaluate the utility of our recommendations by considering a scenario where the recommendation list contains the top \( N \) candidates. Therefore, we adopt precision@N as utility metric since it is widely used to evaluate recommender systems [22, 28]. Precision@N is the number of relevant candidates within the top \( N \) divided by \( N \). Typically, for utility, precision@N is evaluated along with recall@N, which is the number of relevant candidates within the top \( N \) divided by the number of relevant candidates. Since we consider the top \( N \) candidates recommended by the binary vector model as relevant, the number of relevant candidates is also \( N \), hence precision@N and recall@N are identical. That is, we measure the utility only in terms of precision@N.

A drawback of precision is that the order of candidates is not taken into account. Therefore, we additionally use the average precision that is defined as the average of precisions at each rank for a relevant candidate up to rank \( N \). For example, consider a set
of 5 recommended candidates, where the candidates at position 1, 4 and 5 are relevant because they are also in the set recommended by the binary model. The average precision of this list is then given by $(1 + 0.5 + 0.6)/3 = 0.7$. An average precision of 1.0 indicates that all relevant candidates are at the first positions.

### 5.1 Parameter Selection
To implement our recommender system, we need to specify a number of parameters. For the Bloom filters, length $m$ and the number of hash functions $k$ must be specified. To this end, we measure the mean precision@20 of 50 randomly selected jobs over 10 runs with $\epsilon = \ln 3$ to show how $k$ and $m$ affect the utility of bf-DP.

In Figure 3, we plotted the mean precision@20 with $k$ on the x-axis and varying values for $m$. The results generally indicate that a longer Bloom filter leads to more utility and with more hash functions $k$ the precision decreases. We obtain the highest precision with $k = 1$ and $m = 4096$. Therefore, we set the Bloom filter length $m = 4096$, which corresponds to the length of the binary vector.

### 5.2 Privacy-Utility Trade off
We quantify the cost of privacy by comparing bf with bf-DP. Please note that bf does not satisfy the definition of differential privacy. In Figure 4, we present the results for precision@20 (Figure 4a) and average precision (Figure 4b) versus the privacy loss parameter $\epsilon$ for the two models. For all results, we show the mean of 50 randomly selected jobs over 10 runs; standard deviation is used to draw the error bars. Since only bf-DP depends on $\epsilon$, the utility changes with varying $\epsilon$. As expected, the precision@20 as well as the average precision of bf-DP increases with higher $\epsilon$. For a typical $\epsilon = \ln 3$ [9], the precision of bf-DP is below bf. However, for $\epsilon > 7$, the precision@20 of bf-dp approaches the precision of bf. Even for a small $\epsilon = \ln 3$, the average precision is 0.75, i.e., a high proportion of relevant candidates appear early in the recommendation list.

### 5.3 Discussion
Our results demonstrate that Bloom filter can be used to generate recommendations with strong privacy guarantees. With an $\epsilon = 4$, we recommend approximately 75% of the top 20 candidates correctly with an average precision of 0.93. By ensuring LDP, we provide a reciprocal recommender system that is self-determined. Candidates can decide whether to provide their profile. For the sake of clarity, in our evaluation we assumed the same privacy guarantee ($\epsilon$) for each candidate. However, since the unbiased similarity is computed independently for each user, it is possible that each candidate chooses their own desired privacy guarantee. This makes our system more self-determining.

When collecting data over time, the time series can leak information. If noise is repeatedly added to the same or only slightly modified profiles, the noise component can be averaged over a period of time and thus eliminated. This becomes relevant when a candidates profile changes or if a candidate has several similar applied jobs that are independently perturbed. Therefore, repeatable collection of profiles requires an adjustment of the RRT. Otherwise, a profile can be disclosed. Future work should consider longitudinal attacks and make appropriate adjustments such as memoization [11].

Compared to bf-DP, bf provides almost the same accuracy as the binary vector. Since a Bloom filter already provides certain deniability due to bit collisions, we recommend using a Bloom filter instead of a binary vector.

Compared to a centralized approach, the distributed approach has some disadvantages in performance and storage. Due to splitting files into blocks by IPSs and the construction of a Merkle DAG, a storage overhead is introduced. Furthermore, profiles are replicated on multiple devices increasing overall storage requirements. The usage of Bloom filters reduces the size of stored and transferred data, making the data small enough to fit into one block. Since the data fits into one block the additional transfer time due to traversing and finding the DAG can be omitted. An advantage of P2P systems is the self-scalability of data. However, the small data size reduces the benefits due to replication. Future work will concentrate on analyzing and minimizing possible storage and transfer overhead.

## 6 RELATED WORK
Various approaches have been proposed for privacy-preserving recommender systems. They are based on cryptographic primitives [10, 17] or data perturbation [12, 13, 16, 19, 23, 24]. The recommendations, however, are generated using collaborative filtering, which uses preferences of many users to make recommendations. While collaborative filtering is often preferred in terms of accuracy, we use content-based filtering as it provides user-specific classification. That is, recommendations are based on past user preferences, which suits our distributed self-determined approach better. Since it additionally considers the content, it is particularly relevant for reciprocal recommender systems and the application domain considered in this work [14, 15].

Privacy-preserving content-based recommender systems are mostly concerned with targeted advertising [25], where privacy is achieved through anonymization or pseudonymization. However, in a reciprocal recommender system, the use of these approaches would not be feasible since the recommendation is two-sided and therefore the candidates must also be known. Puglisi et al. [22] propose a privacy-preserving content-based recommender by injecting arbitrary keywords into the user profile. In contrast to Puglisi et al., we guarantee LDP for profiles.
Usually, differentially private recommender systems are designed using a centralized architecture [13, 17, 23]. We instead propose a distributed approach that offers self-determined privacy guarantees, using IPFS. In the literature, IPFS is often used in combination with blockchains [26] or to store and exchange data [2, 18]. We use it for content distribution, enabling asynchronous data access.

7 CONCLUSION

In this paper, we present a distributed reciprocal recommendation system. We use Bloom filters to allow local computation of recommendations with differential privacy guarantees. Utilizing IPFS, we allow asynchronous exchange of data increasing users’ control over their data.

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