Private Preferences, Public Rankings: A Privacy-Preserving Framework for Marketplace Recommendations

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Abstract

Protecting user privacy in recommender systems is crucial for fostering trust in marketplaces. In this paper, we propose a privacy-preserving framework that integrates public seller rankings into personalized recommendations without exposing sensitive user preferences. By utilizing "seller representative users" (encoding seller item rankings) and a novel recommendation mechanism, the framework preserves privacy while ensuring robust ranking accuracy. Our approach is validated on multiple use cases extracted from real-world datasets, showing its effectiveness across varying marketplace configurations. This framework is suited for real-world applications, such as e-commerce platforms, where it can enhance user trust, protect sensitive data, and improve engagement by transparently balancing personalization and privacy.

CCS Concepts

• **Information systems** → **Learning to rank**; • **Applied computing** → *Law, social and behavioral sciences.*

Keywords

Recommender Systems, Privacy, Marketplace.

ACM Reference Format:

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1 Introduction

In today's digital marketplace landscape, platforms face a critical challenge: providing personalized recommendations while protecting user privacy. The exponential growth of e-commerce has made personalization essential, yet the sensitive nature of user preferences and behaviors demands robust privacy safeguards [2, 5].

The multi-seller nature of online marketplaces [24] such as *Amazon*, *eBay*, *Alibaba*, *Airbnb*, *Freelancer*, and *Uber* creates unique privacy challenges [3, 19, 23]. For effective recommendation, the central marketplace would traditionally need access to all customers' preferences, including sellers' ratings information. Even with anonymized data, a central platform could potentially match user patterns across sellers, compromising privacy [2]. Consider a healthcare marketplace where users purchase medical supplies from several sellers - combining detailed rating data may inadvertently expose sensitive health information. Similarly, in service marketplaces, merged user preferences can reveal confidential strategies.

Although several recommender systems (RS) have been proposed for marketplace platforms [10, 13, 14], existing approaches face significant privacy challenges. Non-personalized ranking systems [4, 11, 15, 16, 21, 22] rely on generic algorithms that lead to suboptimal user experience. While attribute-based and context-aware methods [1, 20] aim to protect user privacy through predefined categories or situational factors, they often fail to capture nuanced user preferences and may still expose sensitive aggregated data. Alternative privacy-preserving approaches like federated learning require continuous user participation and substantial computational resources, often making them impractical for dynamic marketplaces.

Despite these advances, a significant gap remains in developing marketplace recommendation systems that effectively balance personalization with privacy preservation. Current approaches either compromise on recommendation quality to maintain privacy or risk exposing sensitive user data to achieve better personalization. The lack of solutions specifically designed for multi-seller marketplaces is particularly concerning, as these environments involve complex privacy considerations spanning multiple independent entities. There is an urgent need for frameworks that can leverage publicly available information to enhance recommendations while ensuring user-seller interactions remain confidential [25, 26]. This gap becomes even more critical as privacy regulations tighten globally and users grow increasingly concerned about how their data is shared across platforms. Informally, the question we address in this works is the following: *Can a marketplace leverage sellers' public information to improve recommendations while preventing any seller from accessing users' private interactions with other sellers? In essence, can we enhance recommendation quality without compromising cross-seller user privacy?*

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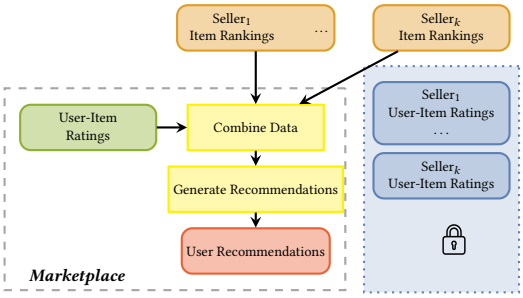

Figure 1: Overview of the proposed RS process within a marketplace environment. The system combines user-item ratings and seller-item rankings from multiple sellers (Seller$_1$ to Seller$_k$). These data is processed to create tailored suggestions for items within the marketplace. Users-sellers interactions are kept private to sellers.

We introduce a novel method combining marketplace ratings with seller rankings to enhance RS while maintaining privacy. By creating "seller representative users" that encapsulate public rankings, we achieve better personalization without exposing private data. As illustrated in Figure 1, our framework consists of three main components (Input Collection, Data Processing, and Recommendation Generation) that will be detailed in Section 2.1. Our contributions include: (i) a privacy-preserving framework for marketplace recommendations that integrates public rankings with user ratings; and (ii) experiments validating our approach across two datasets, three RS, and 18 marketplace scenarios.

Our proposal restricts marketplace access solely to public seller information (item rankings), never requesting private or anonymized seller data. This maintains recommendation utility while protecting sensitive user-seller interactions [5]. Figure 1 summarizes our approach. To our knowledge, this is the first work addressing user-seller interaction privacy in marketplace recommendations while preserving effectiveness and scalability.

2 The Proposed Framework

First, we introduce the notation used in the paper – see Table 1.

Table 1: Notation used throughout the paper.

Symbol	Description
$\mathcal{U}$ / $\mathcal{I}$ / $\mathcal{R}$	Set of users / items / allowed ratings
R	Set of ratings $R \subset \mathcal{U} \times \mathcal{I} \times \mathcal{R}$
r_{ui}	Rating given by user u to item i (where $(u, i, r) \in R$)
r_i	Ranking of item i computed from R
$\mathcal{S}$	Set of sellers $\{S_1, \ldots, S_k\}$ where $k > 1$
M	Marketplace (special seller, $M \in \mathcal{S}$)
$\mathcal{U}^S$	Set of users belonging to seller S
$\mathcal{I}^S$	Set of items belonging to seller S
R^S	Set of ratings given by users to items of seller S

Each rating triple $(u, i, r) \in R$ is unique for each user-item pair, and $\mathcal{S}$ contains exactly one marketplace seller M.

Next, we present a framework designed to generate personalized recommendations for users in a marketplace. It leverages non-personalized item rankings from sellers' platforms. This strategy allows us to augment the recommendations' utility without compromising the privacy of user data held by sellers. By integrating non-personalized seller-centric information, our framework enriches the recommendation process while keeping users' privacy.

2.1 Algorithm Description

Here, we detail the proposed framework, which follows the main steps illustrated in Figure 1. The three major components are:
(1) **Input Collection**: The framework collects two types of input data: (a) User-Item Ratings from the marketplace's own interactions, and (b) Seller Item Rankings from each seller (Seller$_1$ through Seller$_k$) in the form of publicly available aggregated rankings.
(2) **Data Processing**: These inputs are combined through our algorithm that creates seller representative users. For each seller, a virtual user is created who rates items based on that seller's public rankings. This allows integration of seller preference information without accessing private user-seller interactions.
(3) **Recommendation Generation**: The expanded dataset (marketplace ratings plus seller representative users) is processed by the chosen recommender system algorithm to generate personalized recommendations for marketplace users.

The key privacy-preserving aspect is that sellers' private user-item ratings (shown on the right in Figure 1) remain isolated from the marketplace, while only their public item rankings are used.

For instance, consider 5 stars ratings, and a seller S with items i_1 and i_2 with *rankings* as 4.2 and 3.8 respectively. Algorithm 1 creates a seller representative user u_S who rates these items as 5 ⋆ and 4 ⋆ (obtained by $\lfloor 0.5 + r^S_{i_1} \rfloor$ and $\lfloor 0.5 + r^S_{i_2} \rfloor$). This allows incorporating seller preferences while maintaining user privacy.

Algorithm 1 Marketplace Recommender System

1: **input**: set of marketplace ratings given by users to items, $R^M \subset (\mathcal{U}^M \times \mathcal{I}^M \times \mathcal{R})$, sets with sellers items' rankings $\left\{r_i^{S_j} : i \in \mathcal{I}^{S_j}\right\}_{S_j \in \mathcal{S}}$, and a rating estimation method RecSys
2: **output**: set of marketplace rating estimations $\left\{\hat{r}_{ui} : u \in \mathcal{U}^M, i \in \mathcal{I}^M\right\}$
3: **set** $R \leftarrow R^M$
4: **for** each $S_j \in \mathcal{S}$ **do**
5: **create** a fresh user id u, not present in R ▷ new seller representative user representing S_j
6: **for** each $i \in \mathcal{I}^{S_j}$ **do**
7: **set** $R \leftarrow R \cup \left\{\left(u, i, \left\lfloor 0.5 + r_i^{S_j} \right\rfloor\right)\right\}$ ▷ set the seller representative user rating as the seller S_j ranking for item i
8: **end for**
9: **end for**
10: **compute** $\left\{\hat{r}_{ui} : u \in \mathcal{U}^M, i \in \mathcal{I}^M\right\}$ using RecSys to dataset R

The "*meta*" RS in Algorithm 1 takes as input, Step 1, marketplace ratings, sellers' item rankings, and a RS. It outputs estimated ratings for the marketplace, Step 2. For each seller, Steps 4–9, the algorithm creates a new (fresh) seller representative user. Steps 5–9 assign ratings to items based on the seller's rankings, Steps 7, and estimates ratings using the RS method on to the extended dataset, Step 10.

Remark 1. [Privacy by design] *Algorithm 1 operates independently of individual user-seller interactions. It relies solely on marketplace local data and publicly available item rankings, never accessing which users rated which items or their specific ratings across sellers. This design naturally accommodates users rating items from multiple sellers, as all user-item interactions remain private to each seller while the marketplace maintains its own independent feedback system.* ⋄

2.2 Privacy and Complexity Analysis

Our framework safeguards against key privacy vulnerabilities in marketplace environments. As noted in Remark 1, the algorithm operates independently of individual user-seller interactions, accessing only public information. Building on this privacy-by-design foundation, the framework specifically prevents: (*i*) *user profile reconstruction attacks* by ensuring marketplaces cannot reconstruct individual profiles even when combining multiple sellers' rankings; (*ii*) *cross-platform correlation* of user behaviors by limiting data sharing to aggregated item rankings; and (*iii*) protects *sellers' business intelligence* while enabling personalized recommendations without exposing sensitive information.

Now, we detail the computational complexity of Algorithm 1.

Theorem 2.1 (Complexity Analysis). *Algorithm 1's time complexity for a marketplace with $|\mathcal{S}|$ sellers is $O(|\mathcal{S}| \cdot \max_{S\in\mathcal{S}} |\mathcal{I}^S| + f(|\mathcal{U}|, |\mathcal{I}|))$, where $|\mathcal{I}^S|$ is the number of items per seller and the complexity of the chosen recommender system is $f(|\mathcal{U}|, |\mathcal{I}|)$.*

Proof. The algorithm's execution flows through two sequential phases. First, it processes each seller's data to create seller representative user profiles. For each seller in $\mathcal{S}$, the algorithm iterates through their item catalog to assign ratings based on item rankings. This phase requires $|\mathcal{S}|$ iterations over at most $\max_{S\in\mathcal{S}} |\mathcal{I}^S|$ items, yielding a complexity of $O(|\mathcal{S}| \cdot \max_{S\in\mathcal{S}} |\mathcal{I}^S|)$.

The second phase involves generating recommendations using the chosen RecSys method. This step processes the augmented rating matrix containing both marketplace users and seller representative users profiles. Its complexity depends on the specific recommender system employed, represented by $f(|\mathcal{U}|, |\mathcal{I}|)$[1].

The total complexity is dominated by the seller representative user creation phase and the recommendation generation phase, yielding $O(|\mathcal{S}| \cdot \max_{S\in\mathcal{S}} |\mathcal{I}^S| + f(|\mathcal{U}|, |\mathcal{I}|))$. □

3 Experimental Evaluation

We next detail our experimental setup and findings, aiming to formally answer the research question introduced earlier:

RQ *Can a marketplace $M \in \mathcal{S}$ use sellers' ($\mathcal{S} = \{S_1, \ldots, S_k\}$) public information, respecting users privacy, to improve its recommendations to users? I.e., can the marketplace do this and if $r_{ui} \in R^S$ then S' cannot recover r_{ui} for any $S' \neq S$?*

We note that traditional privacy-preserving recommender systems [5] and federated learning approaches [19] were not selected as baselines due to their different underlying assumptions. These methods typically require centralized anonymization, continuous seller-marketplace communication, or computational overhead unsuitable for our multi-seller marketplace scenario. In contrast, our approach uniquely leverages existing public information, making it more practical for immediate deployment in real marketplace environments without architectural changes to seller operations.

[1]For instance, with matrix factorization methods like SVD, this typically involves operations on the user-item matrix.

3.1 Datasets

We use the datasets: MovieLens-100k (ML-100k), with $|R| = 100\,000$ ratings from $|\mathcal{U}| = 943$ users to $|\mathcal{I}| = 1\,682$ items; and MovieLens-1M (ML-1M), with $|R| = 1\,000\,209$ ratings from $|\mathcal{U}| = 6\,040$ users to $|\mathcal{I}| = 3\,952$ items. Our approach would benefit from datasets that better represent our specific scenario. Due to the lack of such datasets, we validated our approach by considering different use-case scenarios, extracted from the two detailed datasets. We use the Root Mean Squared Error (RMSE) to evaluate the ratings' estimation performance of the RS: $\sqrt{\frac{1}{|\mathcal{T}|}\sum_{r_{ui}\in\mathcal{T}}(r_{ui} - \hat{r}_{ui})^2}$, with $\mathcal{T} = \{r_{ui} : (u, i, r) \in \mathcal{U} \times \mathcal{I} \times \mathcal{R}\}$ a test set and $\hat{r}_{ui}$ the estimated rating.

3.2 Recommendation Methods

Here, we illustrate our proposed pipeline to improve recommendation in a marketplace platform, respecting users' privacy, with three RS (SVD [9], SVD++ [8], and NMF [12] – using Python Suprise Scikit tool [7]) and two ranking systems.

Remark 2. [Framework Flexibility] *While we use SVD, SVD++, and NMF in our experiments, our framework supports any recommender system. The same flexibility applies to the ranking systems used.* ⋄

Also, we test as the ranking system the simple arithmetic average of ratings (`Avg`) and the reputation-based ranking system (`Rep`) proposed in [21, 22]. The choice of the later has to do with the resilience to attacks and bribery properties that `Rep` has and the `Avg` does not have [6, 22]. However, disparate reputation issues emerge in Rep, and are dealt with in the proposals of [16–18].

3.3 Data Preparation

Given the absence of publicly available datasets that precisely capture the scenario we are addressing, we resort to simulating the scenario using the aforementioned datasets as follows:

(1) Split the original dataset into 5-fold train/test sets;
(2) Distribute each train set to $k-1$ sellers and the marketplace, with increasing probabilities denoted as $p(i) = \frac{2i}{k(k+1)}$, where $p(k)$ represents the highest probability (i.e., the probability of belonging to the marketplace)[2];
(3) Compute the items' rankings for each seller, allowing for the use of different ranking systems;
(4) Augment the marketplace portion of the train set by introducing a seller representative user (per seller) with ratings equal to the rounded seller rankings (Steps 3–9 of Algorithm 1);
(5) Estimate the missing ratings within the marketplace using an RS, as outlined in Step 10 of Algorithm 1.

Note that other splitting probabilities could be chosen. We opted for this one to mirror the typical imbalance in ratings distribution among sellers. In reality, each seller having an equal number of ratings would be an idyllic scenario. In Figs. 2 and 3, we depict the average number of users, items, and ratings per seller, resulting from the detailed splitting strategy.

[2]Note that $\sum_{i=1}^{k} p(i) = \sum_{i=1}^{k} \frac{2i}{k(k+1)} = \frac{2}{k(k+1)} \sum_{i=1}^{k} i = \frac{2}{k(k+1)} \frac{k(k+1)}{2} = 1$.

Remark 3. *The use-case scenarios' data generation method creates many users in the test set who are not in the marketplace's local train set, making it challenging to design personalized suggestions.* ◇

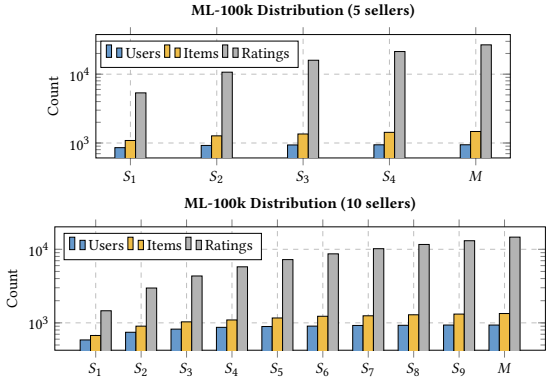

Figure 2: Distribution of users, items, and ratings across sellers in ML-100k dataset for 5-seller (top) and 10-seller (bottom) configurations. M represents the marketplace.

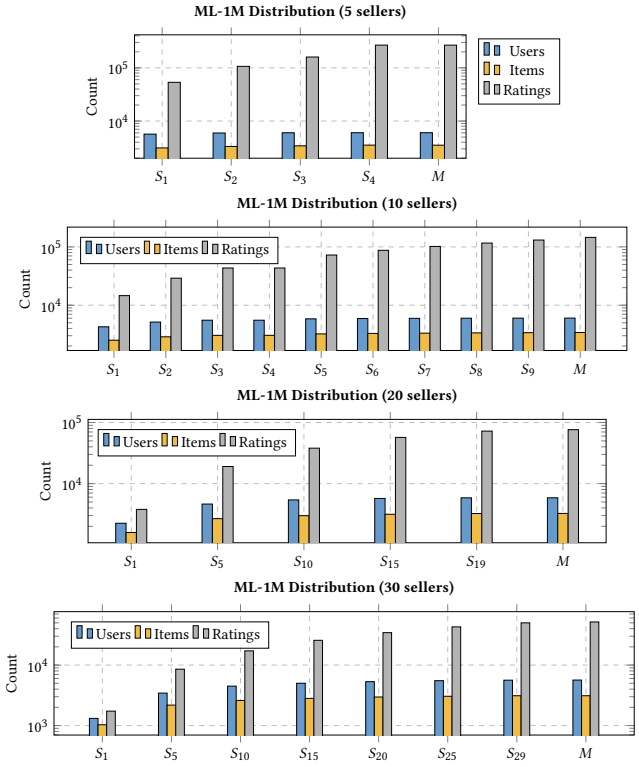

Figure 3: Distribution of users, items, and ratings across sellers in ML-1M dataset for 5-seller, 10-seller, 20-seller, and 30-seller configurations. M represents the marketplace.

3.4 Baselines

To benchmark the obtained results, we use as baseline the recommendations resulting solely from the marketplace platform available ratings. With our proposal, we ensure privacy for each seller's user-item interactions while enhancing recommendations' quality in the Marketplace compared to the baseline. Further, our proposal flexibility accommodates individual ranking and RS for sellers.

3.5 Results

The findings presented in Table 2 provide a positive answer to the research question (RQ). Our proposed method outperforms the baseline in 15 out of 18 experimental scenarios, with RMSE improvements of up to 1.57% (ML-100k, NMF, 9-sellers) and 1.40% (ML-1M, SVD, 29-sellers). Notably, our approach's effectiveness increases with the number of sellers, showing average improvement growth from 0.28% (4-sellers) to 0.83% (29-sellers) in ML-1M. Both ranking systems consistently outperform the baseline, with AVG slightly superior to Rep (0.72% vs 0.64% average improvement), demonstrating our framework's robustness across various marketplace configurations. While a 1.57% RMSE gain appears modest, in large-scale marketplaces such gains can significantly impact user satisfaction and business metrics [26], particularly as seller numbers increase.

Table 2: 5-fold predictions RMSE (↘) for several marketplace setups.

Dataset	Algorithm	Baseline	With Avg (ours)	With Rep (ours)
ML-100k	*4 Sellers*			
	SVD	0.9759±0.0094	**0.9705±0.0074**	0.9720±0.0075
	SVD++	0.9702±0.0093	0.9653±0.0081	**0.9651±0.0079**
	NMF	1.0566±0.0097	1.0530±0.0106	**1.0506±0.0079**
	9 Sellers			
	SVD	0.9957±0.0111	**0.9903±0.0097**	**0.9903±0.0099**
	SVD++	0.9899±0.0113	**0.9840±0.0090**	0.9851±0.0086
	NMF	1.1228±0.0097	1.1116±0.0142	**1.1071±0.0132**
ML-1M	*4 Sellers*			
	SVD	0.9287±0.0011	**0.9266±0.0014**	0.9271±0.0010
	SVD++	**0.9103±0.0016**	0.9154±0.0014	0.9154±0.0025
	NMF	**0.9509±0.0016**	0.9515±0.0021	0.9511±0.0012
	9 Sellers			
	SVD	0.9400±0.0016	**0.9360±0.0015**	0.9365±0.0021
	SVD++	**0.9291±0.0021**	0.9317±0.0014	0.9315±0.0019
	NMF	0.9919±0.0022	0.9896±0.0021	**0.9889±0.0021**
	19 Sellers			
	SVD	0.9544±0.0020	**0.9492±0.0018**	0.9499±0.0017
	SVD++	0.9494±0.0017	**0.9456±0.0020**	0.9464±0.0020
	NMF	1.0500±0.0022	1.0442±0.0038	**1.0420±0.0020**
	29 Sellers			
	SVD	0.9668±0.0016	**0.9616±0.0017**	0.9634±0.0017
	SVD++	0.9616±0.0015	**0.9576±0.0017**	0.9587±0.0018
	NMF	1.0868±0.0016	1.0743±0.0022	**1.0716±0.0026**

4 Conclusions and Future Work

Our work introduces a privacy-aware model for marketplace recommendations, bridging the gap between user personalization and information safeguard. By fusing user ratings and seller rankings, our approach tailors recommendations without compromising privacy, balancing collaborative filtering with seller item quality.

While effective, our framework has several limitations. The reliance on aggregated rankings may not capture nuanced preferences, and the approach assumes honest seller reporting. Additionally, effectiveness depends on the quality of public ranking data. These limitations open several promising research paths: verifying seller-provided rankings without compromising privacy, developing adaptation techniques for temporal preference changes, investigating cross-marketplace collaborations, and studying resilience to attacks. These directions build upon our contributions to advance privacy-preserving recommendations in marketplaces.

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