Practical and Secure Federated Recommendation with Personalized Masks

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Federated recommendation is a new notion of private distributed recommender systems. It aims to address the data silo and privacy problems altogether. Current federated recommender systems mainly utilize homomorphic encryption and differential privacy methods to protect the intermediate computational results. However, the former comes with extra communication and computation costs, the latter damages model accuracy. Neither of them could simultaneously satisfy the real-time feedback and accurate personalization requirements of recommender systems. In this paper, we proposed a new federated recommendation framework, named federated masked matrix factorization. Federated masked matrix factorization could protect the data privacy in federated recommender systems without sacrificing efficiency or efficacy. Instead of using homomorphic encryption and differential privacy, we utilize the secret sharing technique to incorporate the secure aggregation process of federated matrix factorization. Compared with homomorphic encryption, secret sharing largely speeds up the whole training process. In addition, we introduce a new idea of personalized masks and apply it in the proposed federated masked matrix factorization framework. On the one hand, personalized masks could further improve efficiency. On the other hand, personalized masks also benefit efficacy. Empirically, we show the superiority of the designed model on different real-world data sets. Besides, we also provide the privacy guarantee and discuss the extension of the personalized mask method to the general federated learning tasks.

CCS Concepts: • Information systems \rightarrow Recommender systems; • Computing methodologies \rightarrow Mobile agents; • Security and privacy \rightarrow Distributed systems security.

Additional Key Words and Phrases: federated learning, federated recommendation, matrix factorization, secret sharing, personalized mask

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1 INTRODUCTION

In recent years, federated learning has been a fast-growing research field, which keeps private data locally at multiple parties and trains models collaboratively in a secure and privacy-preserving

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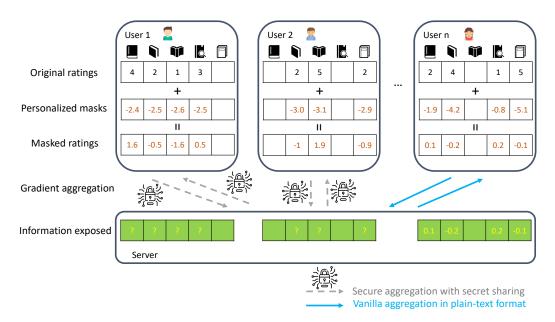


Fig. 1. Illustration of the proposed federated masked matrix factorization (FedMMF) framework. First, each party generates personalized masks via training a local model. Second, masked ratings are constructed via a combination of original ratings and personalized masks. Then, federated matrix factorization is performed on the masked ratings of all parties. The parties with well-protected original data could share model updates via vanilla aggregation in plain-text format. And the other parties carry out secure aggregation with the secure sharing technique. Finally, only the masked ratings leaking no user privacy are exposed to the server.

way [25]. The application scenarios range from cross-device ones [24] to cross-silo ones [34]. The participants of cross-device federated learning are mobile or IoT devices. And reducing communication costs and protecting user privacy are two major concentrations of cross-device federated learning. In contrast, cross-silo federated learning aims to build a model over the data silos of multiple organizations with confidentiality and legal constraints.

Privacy-preserving is one of the major challenges in federated learning. Data decentralization does alleviate privacy risks compared with the conventional data-center training scheme. However, the gradients transmitted among different parties could still leak user privacy [41]. Current solutions can be broadly divided into two categories. The first-kind solutions utilize cryptographic methods such as homomorphic encryption (HE) [12] and secure multi-party computation (SMC) [35]. These methods could lead to lossless model performance. However, they producing extra computation and communication costs since federated learning needs a large amount of calculation and intermediate results exchange. The second-kind solutions utilize the obfuscation methods such as differential privacy (DP) [11]. Although DP-based federated algorithms are efficient, they damage the accuracy of models. Therefore, these solutions all have difficulties when applying to practical problems.

Federated recommender system (FedRec) is an essential application of federated learning in the recommendation scenario [33]. We concentrate on the cross-device horizontal FedRec. Current cross-device horizontal FedRec methods distribute the parameters and training process on both the clients and server, where only gradients are transmitted. The motivation is to keep the user's rating data privately on the local device. Similarly, gradients leak the original data. HE-based FedRec [7] and DP-based FedRec [16] have been designed to provide a recommendation service

without leaking the data privacy of multiple sources. However, they cannot satisfy both the two requirements of recommender system (RecSys), *i.e.*, personalization and real-time.

In this paper, we propose a novel FedRec framework, named federated masked matrix factorization (FedMMF). The designed FedMMF framework could protect the data privacy of FedRec without sacrificing efficiency or efficacy. Instead of using HE and DP, we utilize the secret sharing (SS) technique to incorporate the secure aggregation process of federated matrix factorization. Our designed secure aggregation randomly splits the private gradients of each party into many shares, then reconstructs the final aggregated updates using the secret shares from different parties. Compared with HE, SS largely speeds up the whole training process. In addition, we introduce a new idea of protecting private data from leakage in federated learning, which is called the personalized mask. A personalized mask is a mask that adds on the original data for preserving privacy. "Personalized" means that the mask varies according to the user's data and helps improve model accuracy. Gradients computed on the masked ratings of many participants could be secure enough to directly share with the server, which further relieves the efficiency problem of FedRec. Therefore, on the one hand, the personalized mask could further improve efficiency. On the other hand, the personalized mask also benefits efficacy. We first apply the personalized mask algorithm in the recommendation scenario, specifically in the matrix factorization algorithm [19], because the rating information is the only privacy to protect in the recommendation scenario, which is relatively simple.

Theoretically and empirically, we show the superiority of FedMMF. The personalized masks protect the original rating information, shown in Fig. 1. Thus, the server would access no user privacy. The paper is organized as follows, in Section 2, we first introduce the basic models and the privacy leakage problem; in Section 3, we explain the FedMMF algorithm, the training process, and the privacy guarantee; in Section 4.1, we show the performance of FedMMF in two real-world datasets and talk about the relation between privacy and accuracy; in Section 5, we discuss two related topics in federated learning. They are somewhat similar to our work but differ in the main idea.

The contributions of this paper are three-folded:

- We apply the secret sharing technique in the federated recommendation scenario, which largely speeds up the current federated matrix factorization solutions;
- We propose a new idea of personalized masks and show it could help solve the efficiency and efficacy challenge of FedRec at the same time;
- We discuss related topics and the extension of personalized masks in general federated learning tasks.

2 PRELIMINARIES

In this section, we first introduce the traditional matrix factorization for recommendation. Then, based on the current challenges of RecSys, we explain federated matrix factorization (FedMF). Although FedMF alleviates the privacy problem of FedRec, there still exists leakage in the training process. Finally, we talk about the current solutions to secure FedMF.

2.1 Matrix Factorization

Given a rating matrix $R \in \mathbb{R}^{n \times m}$, the recommender system aims to fill in the missing values of the matrix. Matrix factorization (MF) is regarded as one of the most classic recommendation algorithm [19]. It decouples the original matrix R into two low-rank matrices. The rating r_{ui} that user u gives to the item i can be approximated as:

$$\hat{r}_{ui} = \boldsymbol{q}_i^T \boldsymbol{p}_u, \tag{1}$$

where $q_i \in \mathbb{R}^{k \times 1}$ represents the latent factors of item $i, p_u \in \mathbb{R}^{k \times 1}$ represents the latent factors of user u, and the latent dimension k can be regarded as the item's implicit characteristics. We could optimize the latent factors via minimizing the loss given below using the existing ratings:

$$\min_{\boldsymbol{q}_{i}^{*}, \boldsymbol{p}_{u}^{*}} \frac{1}{2} \sum_{(u, i) \in \mathcal{K}} (r_{ui} - \boldsymbol{q}_{i}^{T} \boldsymbol{p}_{u})^{2} + \lambda (\|\boldsymbol{q}_{i}\|_{2}^{2} + \|\boldsymbol{p}_{u}\|_{2}^{2}), \tag{2}$$

where K stands for the set of user-item pairs whose rating r_{ui} is already known and λ is the regularization coefficient. Stochastic gradient descent is utilized to update each parameter:

$$q_i \leftarrow q_i - \gamma \cdot (\lambda \cdot q_i - e_{ui} \cdot p_u),$$
 (3)

$$\boldsymbol{p}_{u} \leftarrow \boldsymbol{p}_{u} - \boldsymbol{\gamma} \cdot (\lambda \cdot \boldsymbol{p}_{u} - e_{ui} \cdot \boldsymbol{q}_{i}), \tag{4}$$

where $e_{ui} = r_{ui} - q_i^T p_u$ and γ is the learning rate. Conventional recommender systems centrally collect users' private data and train MF algorithm on the server, which leads to immense privacy risks.

2.2 Federated Matrix Factorization

2.2.1 Vanilla FedMF. As the development of federated learning, federated recommender system (FedRec) was proposed to address the privacy and data silo problems in the recommendation scenarios [33]. In this paper, we focus on the horizontal FedRec where each party only contains the rating information of one individual user and the user's private data is not allowed to leave the local device. Federated matrix factorization (FedMF) was designed to train recommendation models in such a naturally distributed situation. In the vanilla FedMF algorithm [3], all the item latent factors $Q \in \mathbb{R}^{m \times k}$ are maintained on the central server, while each user's latent factors p_u is kept on the local party. The training process is as followed and loops until the convergence of model parameters:

Step 1: party u downloads items' latent factors Q from the server

Step 2: party u updates user's latent factors p_u using private local data r_u

Step 3: party *u* computes the gradients of each item's latent factors η_{ui} with r_u and the updated p_u

Step 4: party u sends η_i to server

Step 5: server aggregates the gradients from all users and updates *Q*

2.2.2 Privacy Leakage from Gradients in FedMF. Vanilla FedMF makes sure that users' private data never leaves the local parties. However, the transmitted gradients could also lead to privacy leakage [7]. From user u, the server continuously receives the gradients of the item i's latent vector at step t-1 and step t:

$$\eta_{ui}^{t-1} = \lambda \cdot q_i^{t-1} - e_{ui}^{t-1} \cdot p_u^{t-1},$$
(5)

$$\boldsymbol{\eta}_{ui}^t = \lambda \cdot \boldsymbol{q}_i^t - e_{ui}^t \cdot \boldsymbol{p}_u^t, \tag{6}$$

where $e_{ui}^{t-1} = r_{ui} - \boldsymbol{q}_i^{t-1} \boldsymbol{p}_u^{t-1}$ and $e_{ui}^t = r_{ui} - \boldsymbol{q}_i^{tT} \boldsymbol{p}_u^t$. Besides, the server also knows the update rule of the latent vector of user \boldsymbol{u} :

$$\boldsymbol{p}_{u}^{t} = \boldsymbol{p}_{u}^{t-1} + \gamma \cdot \sum_{i \in \mathcal{K}_{u}} (\lambda \cdot \boldsymbol{p}_{u}^{t-1} - e_{ui}^{t} \cdot \boldsymbol{q}_{i}^{t}), \tag{7}$$

Algorithm 1 Secret Sharing

```
1: CreateShares (s, y, x, l):
2: Randomly choose a_1, a_2, ..., a_{t-1} and set a_0 = s;
3: for j \in \{1, 2, ..., x\} do
4: Compute the ith share of secret s_j = (a_0 + a_1 \cdot j + a_2 \cdot j^2 + ... + a_{y-1} \cdot j^{y-1}) \ mod \ l;
5: end for
6: Return s_1, s_2, ..., s_x.

7: ReconstructSecret (\{(s_j, j)\}, y, x, l):
8: for j \in \mathcal{V} do
9: Construct equation s_j = a_0 + a_1 \cdot (j \ mod \ l) + a_2 \cdot (j^2 \ mod \ l) + ... + a_{y-1} \cdot (j^{y-1} \ mod \ l);
10: end for
11: Solve the equation set and obtain s = a_0;
12: Return s.
```

where \mathcal{K}_u stands for the set of items that user u has rated. Obviously, only \boldsymbol{p}_u^{t-1} , \boldsymbol{p}_u^t and r_{ui} are unknown to the server. Combining equations 5, 6, and 7, the server could solve the unknown variables [21]. In this way, private raw ratings of each user are revealed.

2.2.3 Secure FedMF. To address the gradient leakage problem of vanilla FedMF, a few secure FedMF algorithms have been proposed. For example, HE-based FedMF [7] and DP-based FedMF [16], respectively, utilize HE and DP to further preserve privacy. HE-based FedMF encrypts gradients of item latent factors with HE before transmitting them to the server. Then, the server performs secure aggregation on the encrypted gradients, updates item latent factors in ciphertext state, and distributes the new encrypted item latent factors to each user. In a similar way, DP-based FedMF adds noises to gradients before aggregation. However, the former one causes extra costs and the latter one results in accuracy losses.

3 FEDERATED MASKED MATRIX FACTORIZATION

Neither of the current HE-based FedMF and DP-based FedMF could meet both the personalization and real-time requirements of recommender systems when protecting data privacy. In this section, we explain the proposed federated masked factorization (FedMMF) framework. First, FedMMF applies secret sharing in the secure gradients aggregation procedure, which largely speeds up the training process. Then, we design a new idea of the personalized mask to further alleviate the efficiency and efficacy problem of FedRec.

3.1 Secure Aggregation in FedMMF

In our proposed FedMMF algorithm, we utilize a secure aggregation technique designed with secret sharing (SS) [31] to achieve both efficiency and efficacy of federated learning. This secure aggregation technique was first proposed in [4]. In the following of this subsection, we first introduce the secret sharing method. Then we explain the secure aggregation algorithm with secret sharing.

3.1.1 Secret Sharing. Secret sharing is designed to divide a secret s into x pieces $s_1, ..., s_x$. An adversary with any y pieces or more can obtain the original secret. However, an adversary with any y-1 pieces or fewer cannot. Secret sharing is designed based on polynomial interpolation. The shares' creating and secret-reconstructing processes are shown in Algorithm 1. For an arbitrary

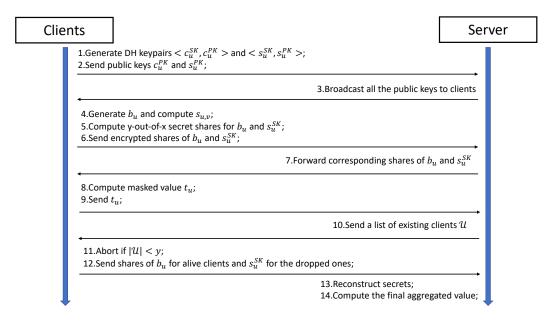


Fig. 2. Details of the secure aggregation protocol with secret sharing. Parties communicate with the server in multiple rounds to get their values aggregated privately. This protocol can be easily extended to the secure aggregation of model parameters and utilized in the federated training process.

secret number s, we could randomly generate x shares $\{(s_j, j)\}$ using a large prime number l based on the CreateShares function. With and only with y and more than y shares, the original secret s can be reconstructed via the ReconstructSecret function.

3.1.2 Secure Aggregation with Secret Sharing. We utilize a secure aggregation method with secret sharing. The details are shown in Fig. 2. Before the aggregation process, all parties agree on the number of users n, the secret sharing threshold t, the large prime number l, the parameters of Diffie-Hellman (DH) method [9], and an arbitrary encryption method for authentication. At the beginning of secure aggregation, each party u generates DH key pairs $< c_u^{SK}, c_u^{PK} >$ and $< s_u^{SK}, s_u^{PK} >$. SK and PK stand for private key and public key, respectively. Then, parties send the public keys to the server. After receiving the public keys from all parties, the server broadcasts them to each party. Next, each party u generates b_u randomly and $s_{u,v}$ for every other party v via the Diffie-Hellman key agreement method. Besides, party u computes secret shares for b_u and s_u^{SK} respectively using the CreateShares function in Algorithm 1. Then, all the parties encrypt the shares using the authenticated encryption method and send them to the server. The server forwards the corresponding shares to each party. After that, each party u computes the masked value t_u for its secret value s_u , shown as below:

$$t_u = (s_u + b_u + \sum_{u < v} s_{u,v} - \sum_{u > v} s_{v,u}) \bmod l,$$
 (8)

where $s_{u,v}$ equals $s_{v,u}$ for a specific pair of public keys (s_u^{PK}, s_v^{PK}) . Next, party u sends its t_u to the server. The server sends the existing party-list \mathcal{U} to all parties. Then, each party u judges if the number of existing parties is larger than y. If so, it decrypts the encrypted shares received in the previous step. Then it sends the share of b_u for the alive parties and the share of s_u^{SK} for the dropped

Algorithm 2 Federated Masked Matrix Factorization (FedMMF)

```
1: Input: r_{u \in \{1,...,n\}}
 2: Output: q_{i\in\{1,\dots,n\}}, p_{u\in\{1,\dots,n\}}, f_{u\in\{1,\dots,n\}}^{mask}

3: Server initializes q_{i\in\{1,\dots,m\}}^0, each party u initializes p_{u\in\{1,\dots,n\}}^0 and f_{u\in\{1,\dots,n\}}^{mask}(\theta_u).
  4: for each party u \in \{1, ..., n\} in parallel do
           // run on each party u
           Train private model f_u^{mask}(\theta_u) on local data r_u;
  6:
           Compute personalized masked rating r_{u,i}^{masked} according to Eq. 11 for each i \in \mathcal{K}_u;
  8: end for
  9: // run on the server
10: for each t = 1, 2, ..., T do
            for each party u \in \{1, ..., n\} in parallel do
                 Get gradients \eta_{ui\in\mathcal{K}_{u}}^{t} = \mathbf{MaskedUpdate}(q_{i\in\mathcal{K}_{u}}^{t-1});
12:
13:
           Get the aggregated gradients \sum_{u \in \mathcal{U}} \boldsymbol{\eta}_{i \in I}^t with secure aggregation protocol in Fig. 2; Update item factors \boldsymbol{q}_i^t = \boldsymbol{q}_i^{t-1} - \boldsymbol{\gamma} \cdot \sum_{u \in \mathcal{U}} \boldsymbol{\eta}_i^t for each i \in I;
14:
17: // run on each party u
18: MaksedUpdate:
19: Compute e_{ui}^t = r_{ui}^{masked} - q_i^{tT} p_u^t for each i \in \mathcal{K}_u; 20: Update user factors p_u^t according to Eq. 7;
21: Compute gradient \boldsymbol{\eta}_{ui}^{t} according to Eq. 6 for each i \in \mathcal{K}_u;
22: Return \boldsymbol{\eta}_{ui \in \mathcal{K}_u}^{t} to server with secure aggregation protocol in Fig. 2.
```

parties to the server. Finally, the server could obtain the aggregated value $\sum s_u$ via the following equation:

$$\sum s_u = \sum t_u - \sum_{u \in \{i\}} b_u + \sum_{u \in \mathcal{U}, v \notin \mathcal{U}} s_{u,v}, \tag{9}$$

where b_u is obtained via the Reconstruct Secret function in Algorithm 1 and $s_{u,v}$ is obtained after s_u^{SK} is reconstructed. Similar to the secret of one single scalar, the above secure aggregation

3.2 Personalized Mask in Recommendation

The additional mask is a common practice of hiding raw data from revealing by other parties in federated learning [34]. It is generated randomly and privately by each party. Like the conventional mask, the main idea of the personalized mask is to cover the original ratings so that the server cannot access users' private data. However, we produce the masks via private well-trained model separately at each party. We name the mask as personalized mask because it can also provide a performance improvement. Shown in Fig. 1, Federated Masked Matrix Factorization (FedMMF) algorithm applies the idea of personalized mask in the previous FedMF architecture. The whole training process is as followed. Firstly, before the federated training of latent factors, each local party u trains a private model using only the user's own data. The corresponding loss function is shown as below:

$$L_u = \frac{1}{|\mathcal{K}_u|} \sum_{i \in \mathcal{K}_u} (r_{ui} - f_u^{mask}(i))^2$$
(10)

Without loss of generality, we define the private model of user u as f_u^{mask} . Then, the model is used to give prediction $f_u^{mask}(i)$ on each user-item pair u, i, where $i \in \mathcal{K}_u$. The opposite of the prediction is regarded as the personalized mask. Finally, all parties collaboratively train a matrix factorization model on the masked rating:

$$r_{u,i}^{masked} = r_{u,i} - f_u^{mask}(i). \tag{11}$$

The prediction of FedMMF algorithm for one specific user-item pair (u, i) is:

$$\hat{r}_{ui} = \boldsymbol{q}_i^T \boldsymbol{p}_u + f_u^{mask}(i). \tag{12}$$

The private model f_u^{mask} could be an arbitrary model which only trains on the local data. Therefore, side information may also be used, which contains user profiles, item attributes, or context features (e.g., location, time, weather, etc.).

On the one hand, We hope for a performance improvement of FedMMF compared to vanilla FedMF. The reason is that we actually utilize the idea of ensemble learning [30]. Ensemble learning is commonly used to combine multiple weak learners for a better prediction performance [8]. On the other hand, the well-behaved private model at each local party could protect the privacy of original ratings. Thus, parties with well-behaved private models are able to directly share their gradients computed on the masked ratings. In such way, the efficiency is further improved.

The details of FedMMF are shown in Algorithm 2. First, each party u trains a private model f_u^{mask} only using local data. Then, personalized masked rating $r_{u,i}^{masked}$ is generated using the private model. Next, federated training is performed on the personalized masked ratings. For each party, the updates of item's latent factors are directly shared to the central server, if the private model is personalized enough to cover the private information. Other parties join the federated training via the secret sharing secure aggregation method 2.

Privacy protection is relatively simple in the recommendation scenarios because we only need to care about the privacy of user ratings. However, when extending the personalized mask technique to general federated learning tasks, we should also prevent feature information from revealing. InstaHide offers us a novel privacy-preserving idea with data augmentation [18]. The authors utilize a simple encryption method to protect the privacy of original image features, while they did not consider the privacy of the label. Combining with the proposed encryption approach, the personalized mask could fulfill the privacy requirement of general federated learning tasks.

3.3 Security Analysis

The task of private model f_u^{mask} is to hide the information of $r_{ui} \in \mathcal{R}$, which is the rating that each user $u \in \mathcal{U}$ gives to item $i \in \mathcal{I}$. For user u, the training data of f_u^{mask} is denoted by $\mathcal{Z}^l = \{(i, r_{ui})\}_{i \in \{1, \dots, l\}}$. The training data is sampled from a joint distribution $P_{\mathcal{I}\mathcal{R}}$. We assume $\mathcal{R} \in [0, 1]$.

Definition 3.1 (Privacy indicator in FedMMF). We define the private information exposed of one specific user u in FedMMF as:

$$J(f_u^{mask}, P_{I\mathcal{R}}) = E_{(I,\mathcal{R}) \sim P_{I\mathcal{R}}} [\|\mathcal{R} - f_u^{mask}(I)\|^2]. \tag{13}$$

This indicator could inform us of many things. It is interpreted in different ways when increasing and decreasing. When indicator J starts to increase from a small number, there are two possible reasons to explain. Firstly, we leak more privacy if the local model is constrained too much. Thus,

the model prediction is approximately the rating bias. In this case, the masks are not secure enough anymore since the bias is much easier to estimate. Secondly, privacy might be protected much better when the model is trained to make random inferences. However, model efficacy is also severely damaged. When indicator J reduces to relatively small numbers, privacy is thought to be protected better. The local private model predicts more accurately, therefore personalized masks cover more information of the original ratings. Theorem 1 provides us how much privacy could be protected the most when privacy indicator J continues decreasing.

THEOREM 1. FedMMF is (ϵ, δ) – private for user u if there exists a function $n_{\mathcal{F}_u} : (0, 1) \times (0, 1) \to \mathbb{N}$. For any $\epsilon, \delta \in (0, 1)$ and any distribution P_{IR} , if $n > n_{\mathcal{F}}$, then

$$Pr_{\mathcal{Z}^{n} \sim P_{I\mathcal{R}}}(J(f_{u}^{mask}, P_{I\mathcal{R}}) \leq \min_{f_{u} \in \mathcal{F}_{u}} J(f_{u}, P_{I\mathcal{R}}) + \epsilon)$$

$$\geq 1 - \delta.$$
(14)

PROOF. For any $f_u \in \mathcal{F}_u$, the privacy indicator of user u calculated on the training sample \mathbb{Z}^n is:

$$J(f_u, P_{IR}^n) = \frac{1}{n} \sum_{i=1}^n \|\mathcal{R}_j - f_u(I_j)\|^2.$$
 (15)

Each $\|\mathcal{R}_j - f_u(I_j)\|^2$ is independent random variable with mean $J(f_u, P_{I\mathcal{R}})$. We further assume that $\|\mathcal{R}_j - f_u(I_j)\|^2 \in [0, 1]$. According to Hoeffding's inequality ¹, we obtain:

$$Pr_{\mathcal{Z}^n \sim P_{I\mathcal{R}}}(|(f_u, P_{I\mathcal{R}}^n) - J(f_u, P_{I\mathcal{R}})| \ge \epsilon) \le 2e^{-2n\epsilon^2},\tag{16}$$

then we could get:

$$Pr_{\mathcal{Z}^{n} \sim P_{I\mathcal{R}}}(\exists f_{u} \in \mathcal{F}_{u}, s.t. | (f_{u}, P_{I\mathcal{R}}^{n}) - J(f_{u}, P_{I\mathcal{R}})|$$

$$\geq \epsilon) \leq 2|\mathcal{F}_{u}|e^{-2n\epsilon^{2}}.$$
(17)

This shows that if

$$n \ge \frac{\log(2|\mathcal{F}_u|/\delta)}{2\epsilon^2},\tag{18}$$

then

$$Pr_{\mathcal{Z}^{n} \sim P_{I\mathcal{R}}}(|(f_{u}, P_{I\mathcal{R}}^{n}) - J(f_{u}, P_{I\mathcal{R}})| \le \epsilon,$$

$$\forall f_{u} \in \mathcal{F}_{u}) \ge 1 - \delta,$$
(19)

which is equivalent to:

$$Pr_{\mathcal{Z}^{n} \sim P_{I\mathcal{R}}}(J(f_{u}^{mask}, P_{I\mathcal{R}}) \leq \min_{f_{u} \in \mathcal{F}} J(f_{u}, P_{I\mathcal{R}}) + 2\epsilon)$$

$$> 1 - \delta.$$
(20)

The reason is that, given

$$\forall f_u \in \mathcal{F}_u, |(f_u, P_{I\mathcal{R}}^n) - J(f_u, P_{I\mathcal{R}})| \le \epsilon, \tag{21}$$

we could obtain step by step:

¹https://en.wikipedia.org/wiki/Hoeffding's_inequality

Dataset	MovieLens 100K	MovieLens 10M	LastFM
No. of users	943	71,567	1,892
No. of items	1,682	10,681	17,632
No. of ratings	100,000	10,000,054	92,834
User profiles	Age, gender, occupation, zip	Tags	Tags
Item attributes	Title, date, genres	Title, genres, Tags	Tags
Item attributes	litle, date, genres	Title, genres, Tags	rags

Table 1. Description of three real-world data sets. Among them, MovieLens 10M contains the most number of users and items. User profiles and item attributes are both prepossessed and combined to be the features of the private context model.

$$\begin{split} J(f_{u}^{mask}, P_{I\mathcal{R}}) &\leq J(f_{u}^{mask}, P_{I\mathcal{R}}^{n}) + \epsilon \\ &\leq \min_{f_{u} \in \mathcal{F}} J(f_{u}, P_{I\mathcal{R}}^{n}) + \epsilon \\ &\leq \min_{f_{u} \in \mathcal{F}} J(f_{u}, P_{I\mathcal{R}}) + \epsilon + \epsilon \\ &= \min_{f_{u} \in \mathcal{F}} J(f_{u}, P_{I\mathcal{R}}) + 2\epsilon. \end{split} \tag{22}$$

Let $\epsilon = \frac{\epsilon}{2}$, we finally get

$$n_{\mathcal{F}_u}(\epsilon, \delta) \le \frac{2\log(2|\mathcal{F}_u|/\delta)}{2\epsilon^2}.$$
 (23)

The function $n_{\mathcal{F}_u}$ determines the sample complexity of user u for training a FedMMF algorithm. It stands for how many samples at least are required to guarantee the privacy of FedMMF for user u. We assume the hypothesis class \mathcal{F}_u is finite. However, it is not a necessary condition, and Theorem 1 can be further generalized. FedMMF is nearly able to achieve the best privacy-preserving performance in \mathcal{F}_u . Therefore, we should always try to find a better hypothesis class for FedMMF to search on different data sets.

4 EXPERIMENTS

In this section, we show that FedMMF could vastly improve model efficiency as well as obtaining good efficacy without the loss of privacy. Firstly, we explain the data sets, baseline models, and other settings in the experiments. Then, we show the improvements of FedMMF on model efficiency. The secret sharing secure aggregation method could promote efficiency well. In addition, with the help of personalized masks, FedMMF further accelerates the training process. At last, we validate the model efficacy improvement of FedMMF with different kinds of personalized masks, comparing to the baseline model.

4.1 Settings

We verify FedMMF on three real-world data sets. Two of them are MovieLens data sets [15], *i.e.*, MovieLens 100K and MovieLens 10M. The other one is the LastFM data set [5]. They are movie and music recommendation data sets, respectively. The detailed descriptions of data sets are shown in Tab. 1. In our experiment, each user is regarded as a participant in the collaborative training process. Therefore, the user's own ratings are kept on the local party. Besides, we utilize the side information (*i.e.*, user profiles and item attributes) to train the local private model. The reason is

that local collaborative filtering algorithms (e.g., local MF) are meaningless and cannot be used to construct personalized masks. Although the involvement of context data could result in unfair comparison more or less, we focus on the illustration of the personalized mask in this relatively simple recommendation scenario in this paper and will generalize to more complicated ones. To construct features from tags in the data set, we utilize TFIDF [29] and PCA [1] techniques. Besides, we set bins for the listening counts of music of the LastFM data set and convert them into ratings scaling from 1 to 5.

The baseline models are shown as below:

- **FedMF** Parties collaboratively train matrix factorization models via sharing the latent factors of common users, where neither HE nor DP is utilized.
- One-order FedMMF Each party locally learns linear personalized masks to hide private rating information via a linear regression model [26]. Then, all parties collaboratively train FedMF on the one-order masked ratings.
- Two-order FedMMF Each party constructs two-order masks to protect private ratings via locally learning a factorization machine model [28]. Then, all parties collaboratively train FedMF on the two-order masked ratings.
- High-order FedMMF Each party captures high-order and nonlinear feature interactions through a neural network model[36]. Then, the private model is utilized to mask local ratings. Finally, all parties collaboratively train FedMF on the high-order masked data.

We do not compare FedMMF with the methods using HE or DP. The reasons are the followings. First, the FedMF algorithms using HE will definitely obtain a same or very close accuracy with vanilla FedMF, but largely slow down the training process. The performances are shown in the previous works [7]. Second, DP has a different privacy definition from ours. Therefore, it's unfair to make such a comparison. Besides, we also show the performance of various local context models and federated context models for reference.

In addition, the evaluation metrics of model efficacy are root mean square error (RMSE) and mean absolute error (MAE). They are averaged by each user-item pair but not each user, which is an alignment with most current works. Besides, we run each experiment 10 times to obtain the mean and standard deviation values.

4.2 Efficiency Promotion and Privacy Discussion

Compared with HE-based FedMF, first, FedMMF largely speeds up the training process of federated learning via secret sharing. At the client side, the computation complexity of our designed secure aggregation method is $O(x^2 + kxy)$, the communication complexity is O(x + ky), and the storage complexity is O(x + ky). At the server side, the computation complexity is $O(kxy^2)$, the communication complexity is $O(x^2 + kxy)$, and the storage complexity is $O(x^2 + ky)$ [4]. Then, the personalized mask technique could further improve the efficiency of the secure aggregation process via sharing plain-text gradients of parties with well-protected ratings.

We provide two attack methods for analyzing how much the personalized mask technique could further promote model efficacy. They are recovery attack and ranking attack. The first one tries to recover the original ratings from the masked ratings, while the second one aims to rank the masked ratings and separate high ratings from low ratings. Taking two-order FedMMF on MovieLens 10M data set as an example, we conduct the attack experiments. The range of ratings in the MovieLens 10M data set is from 0.5 to 5.0. And the rating interval is 0.5.

4.2.1 Recovery Attack. From the masked ratings, an intuitive attack of an adversary is to recover the original ratings. However, the attack could be difficult if only the masked ratings are exposed. Therefore, for each party, we assume that the adversary knows the minimum and maximum values

Recovery rate	$0 \le \alpha < 0.2$	$0.2 \le \alpha < 0.4$	$0.4 \le \alpha < 0.6$	$0.6 \le \alpha < 0.8$	$0.8 \le \alpha \le 1$
g = 1	99%	1%	0%	0%	0%
g = 2	95%	4%	1%	0%	0%
g = 3	66%	28%	5%	1%	0%
g = 4	7%	25%	37%	25%	6%
g = 5	0%	1%	2%	14%	83%

Table 2. The results of recovery attack under different error levels. On the one hand, when error level g is small, the recovery attack could hardly reveal the original rating information. On the other hand, when error level g grows, the recovery attack becomes more accurate. However, the utility of recovered ratings also decreases.

Hit ratio	$0 \le \beta < 0.2$	$0.2 \le \beta < 0.4$	$0.4 \le \beta < 0.6$	$0.6 \le \beta < 0.8$	$0.8 \le \beta \le 1$
h = 0.1	53%	37%	7%	1%	2%
h = 0.3	0%	34%	55%	8%	3%
h = 0.5	0%	0%	41%	52%	7%
h = 0.7	0%	0%	0%	72%	28%
h = 0.9	0%	0%	0%	0%	100%

Table 3. The results of ranking attack under different top proportions. With the masked ratings of each party, the adversary wants to choose the actual high-rated items. When the adversary utilizes a small top proportion h, the attacks performs on most parties achieve a poor hit ratio, which is less than 0.5. Although the hit ratio grows as h increases, a large h results in a useless ranking attack.

of the original ratings. Then, the adversary could scale the masked ratings to the range of original ratings for recovery. We define g as the error level. If the difference between one recovered value and the corresponding original rating is less than α , the recovery is regarded to be successful. Thus, there exists a recovery rate α for each party's masked rating. In Tab. 2, we show the proportion of parties whose recovery rate is in a certain range under different error levels. As we can see, when the error level is small, e.g., g=1 and g=2, the adversary could nearly reveal no party's privacy with a recovery rate larger than 0.5. And as the error level increases, the recovery rate begins to grow. However, a higher error level means a more inaccurate recovery, and the utility of the recovered ratings is poorer.

4.2.2 Ranking Attack. Since the intuitive recovery attack seems not successful enough, we introduce another method named ranking attack. Instead of recovering the original concrete ratings, ranking attack tries to reveal the high-rating items from their masked ratings. First, for each party, the adversary ranks the rated items according to their masked ratings. Then, items in the top h proportion of masked ratings are selected as the high-rating items. Similarly, given h, we also sort these items with regard to their original ratings. Thus, we could evaluate the ranking attack with hit ratio β . It is calculated as the ratio that items selected using masked ratings are in the true high-rating item set. Tab. 3 shows that, under different top proportion h, the ranking attack could reveal the rating ranking privacy of parties. If the selected top proportion is small, e.g., h=1 and h=2, the attacks performed on most parties' masked ratings obtain the hit ratio less than 0.5. It means that more than half of selected items do not have high ratings. When the adversary tunes h

Models	MovienLens 100K		MovienLens 10M		LastFM	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
FedMF	0.9491 ± 0.0040	0.7412 ± 0.0027	0.7753 ± 0.0034	0.5827 ± 0.0015	1.2235 ± 0.0068	0.8780 ± 0.0047
LocalLR	1.0107 ± 0.0025	0.8040 ± 0.0022	0.8818 ± 0.0023	0.6766 ± 0.0011	1.1081 ± 0.0099	0.8163 ± 0.0085
FedLR	1.0796 ± 0.0081	0.8844 ± 0.0058	0.9703 ± 0.0020	0.7497 ± 0.0012	1.5448 ± 0.0110	1.3538 ± 0.0137
One-order FedMMF	0.9340 ± 0.0043	0.7340 ± 0.0035	0.7695 ± 0.0013	0.5808 ± 0.0008	1.0886 ± 0.0109	0.8066 ± 0.0092
LocalFM	1.0083 ± 0.0019	0.8054 ± 0.0019	0.8938 ± 0.0023	0.6862 ± 0.0012	1.0845 ± 0.0130	0.7988 ± 0.0035
FedFM	1.0628 ± 0.0070	0.8644 ± 0.0053	0.9639 ± 0.0022	0.7445 ± 0.0015	1.5301 ± 0.0133	1.3369 ± 0.0117
Two-order FedMMF	0.9218 ± 0.0037	0.7250 ± 0.0030	0.7720 ± 0.0013	0.5827 ± 0.0007	1.0842 ± 0.0090	0.7964 ± 0.0031
LocalNN	1.0114 ± 0.0021	0.8087 ± 0.0017	0.8819 ± 0.0020	0.6816 ± 0.0009	1.1007 ± 0.0068	0.8007 ± 0.0123
FedNN	1.0945 ± 0.0074	0.9176 ± 0.0060	0.9756 ± 0.0024	0.7689 ± 0.0028	1.5461 ± 0.0060	1.3598 ± 0.0075
High-order FedMMF	0.9319 ± 0.0025	0.7317 ± 0.0018	0.7648 ± 0.0016	0.5772 ± 0.0008	1.0860 ± 0.0055	0.7933 ± 0.0070

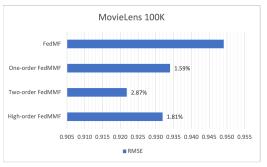
Table 4. Performance of FedMMF compared with baseline models on different data sets. Besides the comparison between FedMMF and FedMF, we also show that FedMMF outperforms local context models and federated context models, which eliminates the effect of feature information incorporated in FedMMF's private models.

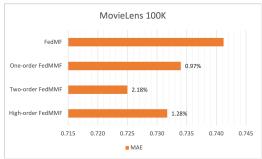
larger, the attack becomes more effective. However, a large h is relatively meaningless because the adversary does not want to choose all items to be high-rating in reality.

According to the experiment results of the above two attack methods, we find that a considerable number of participants get their rating privacy well-protected with the help of personalized masks. Therefore, on the basis of efficiency improvement made by the secret sharing secure aggregation method, the personalized mask could further accelerate the training process of federated recommendation. Besides federated learning, the personalized masked ratings could also be centralized collected and used for training without privacy leakage. This operation is able to reduce the communication and computation cost once again.

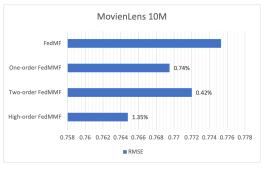
4.3 Improvements on Model Efficacy

In this section, we verify the efficacy of FedMMF on three real-world data sets. The incorporation of personalized masks utilizes the idea of ensemble learning to combine weak learners for a better generalization ability. In the recommendation scenario, feature interactions are important information to capture. Therefore, we implement three private models to construct personalized masks with different properties: the one-order mask, two-order mask, and high-order mask. The performances of FedMMF with these three masks are shown in Fig. 3. RMSE and MAE are both regression evaluation metrics. Smaller value stands for better model efficacy. As we can see, FedMMF models with different personalized masks all outperform FedMF. Another observation is that, on all three data sets, two-order FedMMF and high-order FedMMF dominate alternatively. It means we should utilize cross features to construct personalized masks in the recommendation scenarios. The improvements could be divided into two parts. The first part benefits from the ensemble training scheme of FedMMF, which is our main focus. The second part takes advantage of the side information utilized in the private model of FedMMF. We cannot avoid this unfair improvement with regard to the particularity of recommendation scenarios. This is a compromise because the recommendation scenario is relatively simple with only rating information to protect, and we want to primarily verify the idea of personalized masks. However, we also compare FedMMF models with corresponding local context and federated context models, shown in Tab. 4. Comparing FedMMF with different local context models and federated context models, we could see that FedMMF also outperforms both of them. This observation verifies the main contribution to the efficacy improvement is the incorporation of ensemble learning. On the other hand of the shield,

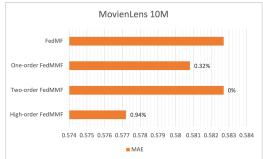




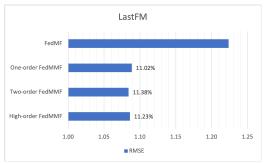
(a) RMSE comparison of models on MovieLens 100K data set.



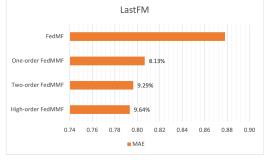
(b) MAE comparison of models on MovieLens 100K data set.



(c) RMSE comparison of models on MovieLens 10M data set.



(d) MAE comparison of models on MovieLens 10M data set.



(e) RMSE comparison of models on LastFM data set.

(f) MAE comparison of models on LastFM data set.

Fig. 3. Experiment results on three real-world data sets. As we could see, FedMMF outperforms FedMF in all cases. Besides, two-order FedMMF and high-order FedMMF dominate alternatively on all the data sets. It means that feature interactions are important in the recommendation scenarios.

FedMMF can also be regarded as an excellent way to combine collaborative information and feature information.

4.3.1 Discussion about Relation between Privacy and Personalization. The efficacy of FedMMF is also related to the privacy of the original ratings of each party. We take the performance of two-order FedMMF on MovieLens 100K data set for illustration. We fix the federated part in FedMMF and tune the hyper-parameters of the local FM model. Fig. 4 shows the relation between RMSE

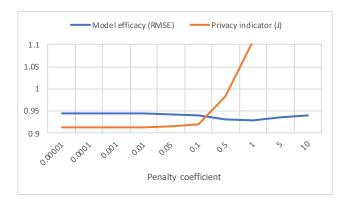


Fig. 4. Illustration of the relation model efficacy and privacy indicator in the experiment of Two-order FedMMF on MovieLens 100K data set. The two variables change with regard to the penalty coefficient of the private model. As we could see, the trends are not the same. Therefore, we should consider more when tuning hyper-parameters of FedMMF.

and privacy indicator J, which is defined in Eq. 15. We could see that, as the penalty of the local model increases, privacy indicator J keeps growing, while RMSE value first goes down then goes up. Large regularization forces the model to learn the rating bias. We regard this case as privacy leakage, as masked ratings could easily reveal private information with our designed recovery attack and ranking attack. When we obtain the best model efficacy of FedMMF, the privacy leakage may be severe. Therefore, we should consider more for training a FedMMF model.

5 RELATED WORKS

In this section, we will introduce two related topics, *i.e.*, personalized federated learning and privacy-preserving federated learning without cryptographic and obfuscation Methods. Besides, we discuss the difference between them and our work.

5.1 Personalized Federated Learning

Personalized federated learning [20, 22, 32] is a new direction of federated learning, personalizing the single global model to get better adaptive to each local party. The motivation is that, in many cases, the single global model cannot outperform local models trained locally. In essence, personalized federated learning addresses the Non-IID problem [40] in federated learning. Current works can be divided into data-based and model-based approaches. Data-based methods aim to align the local data distribution, while model-based methods design different novel federated learning models for better adaptation on each party. For example, [10] train global and local models under regularization with Moreau envelopes. In [39], one specific party only federates with relevant parties, and model parameters are calculated as optimal weighted combinations of available ones based on the relations. [14] aims to find a trade-off between the global federated model and the local private models. Furthermore, [13] provides the first provably optimal method for this personalized federated learning approach.

Several model-based methods also adopt ensemble learning schemes to learn global and local models. [27, 37] utilize the mixture of experts (MoE) technique [23] to combine federated and private models. They both train an extra gating function for deciding which regions to trust one over another. [2] adopts a similar training process as ours. Each party privately trains the local

model. Then, the global model trains on the residuals of all local models. However, none of the above methods studies the privacy-preserving effect of the local model.

5.2 Going beyond Cryptographic and Obfuscation Methods

Privacy protection is an important topic in federated learning. Current privacy-preserving works either utilize cryptographic or obfuscation methods. However, neither of them could maintain efficiency and efficacy simultaneously. Thus, many researchers begin to find new ways besides cryptographic and obfuscation methods

InstaHide and TextHide utilize data augmentation methods to preserve data privacy [17, 18]. InstaHide adopts the Mixup approach [38] to design a simple encryption algorithm. Before federated training, InstaHide performs the proposed encryption on local images. The whole process is efficient and affects little on prediction accuracy. The authors claim InstaHide can well protect data privacy. However, [6] provides an attack that can successfully break the InstaHide encryption and reveal user privacy. Similarly, TextHide applies the same encryption logic in the NLP tasks. InstaHide and TextHide are data-based privacy-preserving approaches, while FedMMF could be regarded as model-based. Furthermore, our proposed personalized mask approach is beneficial to model efficacy.

6 CONCLUSION

In this paper, we provide a new idea of personalized masks to protect data privacy in federated learning, which neither slows the training process down nor damages model performance. Taking the recommendation scenario as an example, we apply it in the FedMMF algorithm. Combining with the secure aggregation method of secret sharing, the proposed model shows superiority theoretically and empirically. In our future work, we would like to extend personalized masks to general federated learning tasks that involves feature information in the collaborative process.

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